MINISTRY OF EDUCATION AND SCIENCE OF UKRAINE
STATE UNIVERSITY "KYIV AVIATION INSTITUTE"
Faculty of Air Navigation, Electronics and Telecommunications
Department of Aviation Computer-Integrated Complexes

ADMIT TO DEFENCE
Head of Graduation Department
________ Viktor SINEGLAZOV
"___"_______________2025.

QUALIFICATION WORK
(EXPLANATORY NOTE)

GRADUATE EDUCATIONAL DEGREE

"BACHELOR"

Specialty 151 "Automation, computer-integrated technologies and robotics»
Educational and professional program «Information technology and engineering of aviation computer systems»

Theme:Intelligent high-resolution image generation system

Executor: applicant for higher education Maksym Tarnovetskyi
Supervisor: senior lecturer, Ph.D., Serhii Dolhorukov

Standard controller: _________ Filyashkin M.K.
(signature)

Kyiv– 2025

МІНІСТЕРСТВО ОСВІТИ І НАУКИ УКРАЇНИ
ДЕРЖАВНИЙ УНІВЕРСИТЕТ «КИЇВСЬКИЙ АВІАЦІЙНИЙ ІНСТИТУТ»
Факультет аеронавігації, електроніки та телекомунікацій
Кафедра авіаційних комп’ютерно-інтегрованих комплексів

ДОПУСТИТИ ДО ЗАХИСТУ
Завідувач випускової кафедри
________ Віктор СИНЄГЛАЗОВ
“___”_______________2025 р.

КВАЛІФІКАЦІЙНА РОБОТА
(ПОЯСНЮВАЛЬНА ЗАПИСКА)

ВИПУСКНИКА ОСВІТНЬОГО СТУПЕНЯ

“БАКАЛАВР”

Спеціальність 151 «Автоматизація та комп’ютерно-інтегровані технології»
Освітньо-професійна програма «Інформаційні технології та інженерія авіаційних комп’ютерних систем»

Тема: Інтелектуальна система генерації зображень високої роздільної здатності

Виконавець: здобувач вищої освіти Тарновецький Максим Васильович

Керівник: ст. викладач, к.т.н. Долгоруков Сергій Олегович

Нормоконтролер: _________ Філяшкін М.К.
(підпис)

Київ – 2025

STATE UNIVERSITY "KYIV AVIATION INSTITUTE"
Faculty of Air Navigation, Electronics and Telecommunications
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Educational degree: Bachelor
Specialty 151 "Automation and computer-integrated technologies"
Educational and professional program "Information Technology and Engineering of Aviation Computer Systems"

APPROVE
Head of Department
_________ Viktor SINEGLAZOV
“____” _______2025.

TASK

to perform the student's qualification work

Maksym Tarnovetskyi

1. Topic: "Intelligent high-resolution image generation system".

2. Term of work: 01.05.2025 until 12.06.2025.

3. Initial data for work: Dataset with dermatoscopic images of ISIC-2019; Deep Revolutionary GAN (DCGAN) architecture. Results of scientific publications in the field of medical informatics and computer vision.

4. Content of the explanatory note (list of issues to be developed): 1. Analysis of skin cancer types and features; 2. Analysis of methods of diagnosis and classification of skin lesions; 3. Theoretical justification used generative adversarial networks (GANs); 4. Development and implementation of the DCGAN architecture to generate images of cutaneous lesions; 5. Constructing a classifier based on the DCGAN discriminator; 6. Image generation quality analysis and evaluation of classification accuracy.

5. List of mandatory graphic material: 1. Block diagram of DCGAN architecture; 2. Classification subsystem structure; 3. Depiction of examples of synthesized and classified dermatoscopic images; 4. Graphs of generator and discriminator loss functions; 5. Confusion matrix; 6. ROC curve plot and other quality metrics.

6. Schedule schedule:

№ п/п	Task	Deadline	Performance mark
1.	Analysis of scientific literature on the topic	01.05.2025	
2.	ISIC-2019 data preparation	02.05.2025	
3.	Development of DCGAN core architecture	03.05 – 06.05.2025	
4.	Generating synthetic images	07.05 – 09.05.2025	
5.	Adapting the discriminator for classification	10.05 – 12.05.2025	
6.	Classifier Training	13.05 – 15.05.2025	
7.	Analysis of metrics, visualization of results	16.05 – 18.05.2025	
8.	Comparison with other approaches	19.05 – 21.05.2025	
9.	Execution of the explanatory note	22.05 – 25.05.2025	
10.	Review, preparation for protection	26.05 – 31.05.2025	
11.	Preparation of presentation	01.06 – 12.06.2025	

7. Task issue date ____

Supervisor: ______________________________Serhii DOLHORUKOV

Task accepted for execution ___________Maksym TARNOVETSKYI

____ ” ________2025 .

ДЕРЖАВНИЙ УНІВЕРСИТЕТ «КИЇВСЬКИЙ АВІАЦІЙНИЙ ІНСТИТУТ»

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Кафедра авіаційних комп'ютерно-інтегрованих комплексів

Освітній ступінь: бакалавр

Спеціальність 151 «Автоматизація та комп'ютерно-інтегровані технології»

Освітньо-професійна програма «Інформаційні технології та інженерія авіаційних комп'ютерних систем»

ЗАТВЕРДЖУЮ

Завідувач кафедри

_________ Віктор СИНЄГЛАЗОВ

“ ____ ” _______2025 р.

ЗАВДАННЯ

на виконання кваліфікаційної роботи студента

Тарновецького Максима Васильовича

1. Тема роботи:«Інтелектуальна система генерації зображень високої роздільної здатності».

2. Термін виконання роботи: з 01.05.2025 р. до 12.06.2025 р.

3. Вихідні дані до роботи: Датасет з дерматоскопічними зображеннями ISIC-2019; Архітектура Deep Convolutional GAN (DCGAN). Результати наукових публікацій у сфері медичної інформатики та комп'ютерного зору.

4. Зміст пояснювальної записки (перелік питань, що підлягають розробці): 1. Аналіз типів та особливостей раку шкіри; 2. Аналіз методів діагностики та класифікації уражень шкіри; 3. Теоретичне обґрунтування використання генеративних змагальних мереж (GAN); 4. Розробка та реалізація архітектури DCGAN для генерації зображень шкірних уражень; 5. Побудова класифікатора на основі дискримінатора DCGAN; 6. Аналіз якості генерації зображень та оцінка точності класифікації.

5. Перелік обов'язкового графічного матеріалу: 1. Блок-схема архітектури DCGAN; 2. Структура класифікаційної підсистеми; 3. Зображення прикладів синтезованих та класифікованих дерматоскопічних зображень; 4. Графіки функцій втрат генератора і дискримінатора; 5. Матриця змішування (confusion matrix); 6. Графік ROC-кривої та інші метрики якості.

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6. Календарний план-графік:

№ п/п	Завдання	Термін виконання	Відмітка про виконання
1.	Аналіз наукової літератури з теми	01.05.2025	
2.	Підготовка даних ISIC-2019	02.05.2025	
3.	Розробка базової архітектури DCGAN	03.05 – 06.05.2025	
4.	Генерація синтетичних зображень	07.05 – 09.05.2025	
5.	Адаптація дискримінатора для класифікації	10.05 – 12.05.2025	
6.	Навчання класифікатора	13.05 – 15.05.2025	
7.	Аналіз метрик, візуалізація результатів	16.05 – 18.05.2025	
8.	Порівняння з іншими підходами	19.05 – 21.05.2025	
9.	Оформлення пояснювальної записки	22.05 – 25.05.2025	
10.	Рецензування, підготовка до захисту	26.05 – 31.05.2025	
11.	Підготовка презентації	01.06 – 12.06.2025	

7. Дата видачі завдання ____

Керівник: ____ Долгоруков С.О.

Завдання прийняв до виконання ________________ Тарновецький М.В.

____ ” _______2025 р.

ABSTRACT

The explanatory note of the qualification work "Intelligent high-resolution image generation system" contains 98 p., 27 Fig., 13 Tabl., 26 sources.

Keywords: artificial intelligence, deep learning, DCGAN, image generation, classification, skin cancer, dermatoscopy, binary classifier.

The object of research is the process of diagnosing skin cancer using deep learning methods.

The subject of the study is generative adversarial networks and modification of the DCGAN discriminator for the classification of dermatoscopic images.
Objective: To develop an intelligent medical system for the automatic classification of benign and malignant skin formations using DCGAN.

Research methods - analysis of modern scientific sources, data processing from a set of ISIC-2019, construction and training of deep convolutional neural networks, generation of synthetic images, modification of the discriminator architecture, calculation of classification accuracy metrics (precision, recall, F1-score, AUC).

In the theoretical part of the work, a review of the types of skin diseases, diagnostic methods and approaches to the use of generative models in medical informatics is carried out. The practical part includes the development of the DCGAN architecture, the creation of a dermatoscopic image generator and the use of a discriminator as a binary classifier.

The results of the studies indicate the effectiveness of the approach: the system has reached high values of metrics in classification (for example, Recall for the malignant class is more than 90%). The proposed model allows to improve the accuracy of preliminary diagnosis of skin cancer without the need for complex physical testing.

The results of the qualification work can be used in medical IT systems, to train artificial intelligence in conditions of limited data sets and further improve computer diagnostics in dermatology.

РЕФЕРАТ

Пояснювальна записка кваліфікаційної роботи «Інтелектуальна система генерації зображень високої роздільної здатності» містить 98 п., 27 рис., 13 табл., 26 джерел.

Ключові слова: штучний інтелект, глибинне навчання, DCGAN, генерація зображень, класифікація, рак шкіри, дерматоскопія, бінарний класифікатор.

Об'єктом дослідження є процес діагностики раку шкіри за допомогою методів глибокого навчання.

Предметом дослідження є генеративні змагальні мережі та модифікація дискримінатора DCGAN для класифікації дерматоскопічних зображень.

Мета: Розробити інтелектуальну медичну систему для автоматичної класифікації доброякісних і злоякісних утворень шкіри з використанням DCGAN.

Методи дослідження - аналіз сучасних наукових джерел, обробка даних з набору ISIC-2019, побудова і навчання глибоких згорткових нейронних мереж, генерація синтетичних зображень, модифікація архітектури дискримінатора, розрахунок точності класифікації метрик (точність, відкликання, F1-score, AMУ).

У теоретичній частині роботи проведено огляд видів шкірних захворювань, методів діагностики та підходів до застосування генеративних моделей у медичній інформатиці. Практична частина включає в себе розробку архітектури DCGAN, створення дерматоскопічного генератора зображень і використання дискримінатора як бінарного класифікатора.

Результати досліджень свідчать про ефективність підходу: система досягла високих значень метрики в класифікації (наприклад, Recall для злоякісного класу становить більше 90%). Запропонована модель дозволяє підвищити точність попередньої діагностики раку шкіри без необхідності проведення комплексного фізичного тестування.

Результати кваліфікаційної роботи можуть бути використані в медичних IT-системах, для навчання штучного інтелекту в умовах обмежених наборів даних і подальшого вдосконалення комп'ютерної діагностики в дерматології.

CONTENTS

INTRODUCTION

In the modern world, artificial intelligence (AI) is one of the most intensively developing fields of science and technology. Its ability to self-learn, adapt to new situations, process large amounts of data and make decisions based on complex models has opened unprecedented opportunities for the intellectualization of systems in various spheres of human activity. One of the most promising areas of application of AI is medicine - an industry where accuracy, efficiency and individualized approach play a key role. These characteristics allow us to consider artificial intelligence as a powerful tool in the diagnosis and treatment of complex diseases, in particular cancer.

Special attention deserves skin cancer - one of the most common cancer in the world. Each year, more than a million new cases of this disease are recorded, and although early diagnosis allows it to be completely cured, timely detection is often a difficult task. The main challenges in the fight against skin cancer are the similarity of malignancies to benign ones, the subjectivity of visual assessment by a doctor, and the limited availability of highly qualified dermatologists in rural or sparsely populated regions. All this justifies the need to create automated diagnostic systems based on artificial intelligence that can reduce the burden on medical personnel and increase the accuracy of the initial detection of the disease.

The application of deep convolutional neural networks (CNNs) as well as generative adversarial networks (GANs) to generate synthetic images of skin lesions and their subsequent classification is an innovative field in medical informatics. In particular, the Deep Revolutionary Generative Adversarial Network (DCGAN) architecture allows not only to model realistic images, but also to use the discriminator as a pre-trained classifier for recognizing types of lesions. This opens up prospects both for expanding training samples in tasks with a limited amount of data (data augmentation), and for building full-fledged diagnostic systems.

The aim of this thesis is to develop an intelligent medical diagnostic system for the classification of skin cancer based on the DCGAN generative model. The main tasks are the analysis of modern approaches to the diagnosis of skin cancer, the study and implementation of the DCGAN architecture, the generation of synthetic images of skin lesions, the training of the discriminator on the classification of cancer types, as well as the assessment of the accuracy of the constructed system.

The relevance of the topic is due to the need to increase the effectiveness of diagnostics in the field of dermatology, especially in conditions of limited access to specialists. The use of deep neural networks allows you to automate the process of analyzing dermatoscopic images, reduce the likelihood of erroneous interpretation of results and contribute to personalizing the approach to the patient.

With the rapid development of deep learning, more and more studies devoted to generative models appear in the world. A special place among them is occupied by generative adversarial networks (GANs), which allow you to create new, previously non-existing data, while maintaining the statistical and visual properties of the original set. This is especially valuable in medicine, where there is often a problem of insufficient number of qualitatively marked images. For example, in the case of rare forms of skin cancer or when it is necessary to balance classes in classification tasks.

The diploma project focuses on combining the generative component (creation of images of skin pathologies) with the classification one (identification of the type of lesion), which allows creating a two-component system with the possibility of further adaptation to real clinical scenarios. It is especially important that the use of a discriminator as a classifier allows you to reuse an already trained network without the need for full training of a new model, which significantly reduces computational costs.

Also within the framework of the work, a comparative analysis of the results will be carried out with other approaches described in modern scientific articles, which will allow assessing the advantages and disadvantages of the chosen DCGAN architecture. This approach forms the scientific basis for further research and improvement of computer diagnostics technologies in the field of oncodermatology.

As a result, the presented system is not only a technical tool, but also an example of effective integration of knowledge in computer science, medicine and artificial intelligence, which meets modern requirements for multidisciplinary research. Work on this project is an important step in the training of a digital specialist who is able to influence the development of healthcare by introducing innovative solutions.

CHAPTER 1.
SKIN CANCER AND ITS SIGNS

1.1. Definition of skin cancer and classification of its types

Skin cancer is a disease that is accompanied by uncontrolled growth of abnormal cells in the tissues of the skin. The disease can occur in people with any skin tone.

Cancer mostly develops in areas exposed to the sun, including the scalp, face, lips, ears, neck, and chest. Also, skin cancer is one of the most common forms of oncology on the hands and feet. Skin that is usually not exposed to ultraviolet radiation (for example, skin in the genital area) is less prone to oncology.

Types of skin cancer

There are three main and several less common types of pathology. The main types of skin cancer include:

- melanoma (formed in cells called melanocytes). Melanocytes produce melanin - a brown pigment that determines the shade of the skin and the degree of its protection from ultraviolet radiation;
- squamous cell carcinoma (epithelioma), which develops in the cells of the squamous epithelium of the outer layer of the skin. One form of epithelioma is papillary skin cancer. At the initial stage, the symptoms of skin cancer, accompanied by the appearance of malignant papillomas, can coincide with the manifestations of non-cancerous neoplasms, which complicates the diagnosis. Prognosis in squamous cell corneal skin cancer is more favorable compared to aggressive non-corneal type of oncology;
- basal cell carcinoma (basaloma), which is formed in the basal cells of the lower part of the epidermis (the outer layer of the skin).

Basal cell carcinoma (SCC)

Basalioma is one of the most common skin malignancies that develops from altered epidermal cells. Also there are such names of the disease: "basal cell carcinoma," "carcinoma." The tumor grows slowly, very rarely metastasizes, but can affect neighboring tissues, organs, even bones, destroying them. Most often, the neoplasm is localized in the region of the eyelids, wings of the nose, temples, auricles, less often - on the neck, trunk and limbs. The disease can recur after proper and timely treatment.[1]

Fig. 1.1. Example of Basalioma [1]

Classification

Experts distinguish several species and subspecies of basalioma. Formations can be burgundy, whitish, red or pink. Tumors change size, shape and shade. It is believed that a small growth with clear contours is safer.

According to clinical manifestations, the following types of skin tumors are distinguished:

- Nodal. They have a small size with a uniform structure, a translucent shade with vascular "stars," the most common. The patient does not experience any discomfort, so rarely pays due attention to the spot. The growth is localized on the neck and face.
- Ulcerative. Arise as a result of the development of the nodular form. The focus of the tumor grows and ulcers appear, covered with necrotic and purulent crusts.
- Superficial. Grow slowly, do not disturb a person for years, seemingly flat formations of different shades of red with uneven edges.

- Flat. It proceeds aggressively, scleroderma-like basal cell sometimes affects soft tissues, rarely there is the formation of ulcers, in clinical manifestations similar to eczema and psoriasis.
- Metatypical. Combine the symptoms of squamous cell and basal cell carcinoma. The form is very aggressive, spreads and metastases to distant tissues, organs.
- Infiltrative. Occur with the progression of nodular and flat forms. In this type of skin cancer, the risk of rapid development of the disease with the growth of the tumor deep, metastasis and relapses after therapy is increased.
- Pigmented. Appear on the skin in the form of flat spots with high pigmentation in the center and along the edges. The growth is covered with sores with pus, which heal, leaving behind dark spots.
- Warty. Resemble a wart, clearly rises above the skin, have a grayish tint. Formation without ulcers and vascular "stars."
- Probing. Damage the integrity of the skin, grow in areas that are prone to injury. The tumor is covered with a crust, along the edges you can see a tissue of pink color.
- Fibroepithelioma Pincus. It often develops on the lower back, a rare form, has the appearance of a fibrous polyp on the leg, can take a hemispherical shape.

The most common are nodular, superficial and morpheoform neoplasms.

Nodular basalomas are accompanied by the appearance on the skin of small, shiny, hard, translucent or pink protruding nodules with vessels, crusts and ulcers. Usually basaliomas occur on the face or in other areas exposed to the sun.

Superficial basaliomas can develop as red or pink, fringed, thin papules or plaques (usually on the trunk). At the initial stage, superficial basal cell skin cancer can manifest as pink spots, which as they grow become similar to psoriasis or localized dermatitis.

Morpheoform basaliomas are flat, flattened plaques that can have a flesh or light red color, fuzzy borders and complemented by scars.

Pigment-producing tumors are called pigmented basal cell carcinomas. Other types of skin malignancies include Kaposi's sarcoma, Merkel's carcinoma, sebaceous carcinoma, and exploding dermatofibrosarcoma.

The disease proceeds in 5 stages:

- zero - the growth is not yet formed, but cancer cells develop in the body;
- the first - a spot appears on the skin up to 2 cm;
- the second - the tumor reaches a size of up to 5 cm;
- third - the formation begins to express and germinates deep;
- fourth - there are multiple ulcers and large growths that destroy the bone structure, cartilage, organs.

The prognosis is favorable for stages 1 and 2. In other cases, relapses and scars after treatment are possible.

Etiology of Basalioma

The exact causes of basalioma are unknown, they are divided into mandatory and relative. There are a number of factors that can trigger skin cancer. At risk are people over the age of 40.

Mandatory precancerous pathologies include:

- Bowen's disease.

  Occurs with prolonged chemical, ultraviolet radiation, human papillomavirus.
- Paget's disease.

  Synonymous with breast cancer, develops in women and men after 50 years.
- Xeroderma pigment.

  Genetic skin pathology caused by irreversible changes in the epithelium due to ultraviolet radiation.
- Keir's erythroplasia.

  An inflammatory disease that affects the genitals.

Relative precancerous pathologies include:

- Keratoacanthoma.

  Benign neoplasm of epithelial tissue.
- Radial ulcers.

  Damage to the epidermis by ionizing radiation.
- Seborrheic acanthoma.

  Senile keratosis, senile keratosis, occurring in places that are regularly irritated by friction; the tumor develops into basal cell no more than 7% of cases.
- Trophic ulcers.

  Occur against the background of diabetes, thrombosis, atherosclerosis.
- Solar keratosis.

  It develops with intensive insolation and hereditary predisposition.
- Skin horn.

  In 25% of cases, the disease causes basal cell carcinoma.
- Granulomas, syphilitic rubber.

  With a prolonged course of syphilis, metaplasia occurs, which is a precancerous condition.
- Cold abscess.

  Develops in secondary tuberculosis and incorrect BCG vaccination; ulcers and fistulas do not heal for a long time, provoking the degeneration of tissues into cancerous ones.
- Keloid scars.

Pathogenesis

Skin cancer lasts a long time, especially with a superficial form. Education is constantly increasing. In the early stages of symptoms is not expressed - there is a small bubble of pink-gray color. When touched, a dense build-up covered with a crust is felt. Possible appearance of ulcers, erosive areas.

At the zero and first stage, the formation is small (up to 2 cm), does not pass to neighboring areas. On the second - the tumor germinates to the entire thickness of the epidermis and exceeds the size of 20 mm. On the third - the growth extends to soft tissues. The last stage is characterized by damage to cartilage, adjacent tissues, organs and bones. Severe complications occur when the pathology spreads to the ears, brain, bones and eyes.

Symptoms of Basalioma

The disease is asymptomatic, with the exception of the appearance of tumors on the skin. At first it is small, similar to a pimple or mole. Then the tumor increases, in the center there is an ulcer, which is covered with a crust. If you remove it, a depression appears, again covered with a crust. A dense roller forms around the neoplasm. When stretching the skin, it is easy to notice. The roller consists of small bubbles, similar to pearls.

In some cases, new nodules develop, merging with each other. Due to vasodilation, "vascular asterisks" appear. An ulcer occurs in the center, it increases and partially scars. Over time, the tumor germinates deeper, causing pain and itching. The edges can be clear, uneven or in the form of a hemisphere. Signs of basalioma are not detected, so the disease is diagnosed in advanced stages.

Treatment of Basalioma

In the treatment of basalioma, several types of therapy are used. Sometimes, with a tumor size of up to 7 mm, the local use of chemotherapy drugs (cytotoxic) is prescribed.

Other treatments:

- Electrocoagulation. Effects on the tumor of high frequency current at which cancer cells are burned out. The method is reliable, but is not used for treatment on the face, since after therapy a scar remains.
- Cryodestruction. Neoplasm freezing with liquid nitrogen. The procedure is painless, leaves no scars, is used for superficial localization of the tumor, does not exclude relapses.

- Laser removal. Suitable for treatment on the face and the elderly, because it leaves no traces, does not cause complications. Before the procedure, the skin is anesthetized.
- Radiation therapy. Destruction of cancer cells by beta rays or near focal radiotherapy. Accelerated electrons do not damage healthy tissue, do not penetrate very deep into the epidermis. There may be several courses until the tumor completely disappears.
- Phototherapy. Effect on neoplasms by light radiation. The doctor applies special applications or ointment to the tumor and directs a lamp to it. The method starts the production of free radicals that damage the cancer cells and the growth dies. The procedure does not leave scars, scars.

If the tumor has sprouted into deep layers, several methods of therapy are used.

Epithelioma

Epithelioma is the common name for neoplasms growing from cells of the flat or glandular epithelium in the skin layer. Often formations are benign, but there are cases of degeneration of growths into squamous cell carcinoma under the influence of certain factors. Conditionally safe epitheliomas are adenoma, papilloma. Malignant skin formations - adenocarcinoma, basal cell, melanoma, carcinoma.

The danger of epithelioma lies not only in the risk of rebirth. Often, formations grow inward, putting pressure on blood vessels, joints and nerve nodes. This can lead to malfunction and failure of organs, systems. Therefore, supervisory tactics are rarely chosen. Doctors prefer to treat this pathology immediately after detection and refined diagnosis.[2]

Causes of epithelioma

The causes of the development of epithelium are not fully understood. Dermatologists tend to believe that the risk of formation of intradermal pathologies from epithelial cells is higher in people who are under the influence of the following factors:

— negative effect of UV - prolonged exposure to the sun, frequent sunburn, visiting a solarium;
— chemical and thermal burns of the skin;
— exposure to radiation exposure;
— exposure to viruses and bacteria;
— hormonal imbalance;
— frequent trauma to the skin;
— exposure to chemicals.

Possible formation of skin pathologies in people prone to allergic manifestations with frequent contact with the allergen. The heredity factor is not confirmed, although not excluded.

How epithelioma manifests itself

Fig. 1.2. Epithelioma example [2]

Pathology has many clinical forms. Most neoplasms from epithelial tissue appear in the form of small tubercles, irregularly shaped seals, which grow over time, increase in size. Location - surface or thickness of the skin, mucous membrane. Color - white, blue, yellow. Often, such neoplasms, for example, pilomatrixoma or spinocellular epithelioma, appear in adulthood and older age. In addition to the Malerba epithelioma. This education develops in children.

Epithelioma: treatment

The only method of treating this pathology is surgical removal of the neoplasm. A benign skin epithelioma is removed by a dermatologist. Malignant formations require the treatment of an oncologist.

Previously, the only treatment was surgical excision, after which a large scar remained on the skin. Today, minimally invasive methods are used. An aesthetically effective method of removing benign skin formations with a laser is practiced. It allows you to deprive patients of epithelium without the risk of recurrence, without bleeding. The risk of wound infection and scarring at the site of action is excluded. Laser radiation completely evaporates pathogenic cells and kills infectious agents. The procedure is performed under local anesthesia.

Melanoma [3]

Melanoma is a malignant tumor that develops from melanocyte pigment cells. This cancerous tumor most often begins its development on the skin or mole. Rarely in skin cancer, localization is manifested in other organs, such as the eyeball, the mucous membrane of the oral cavity or the undergrowth. One of the most dangerous human malignant tumors, characterized by frequent relapses and metastasizing lymphogenic and hematogenic processes.

Fig. 1.3. Melanoma example [3]

Classification of melanoma

Clinical forms of malignant melanoma:

- Surface-spreading.

  In women, it appears on the legs, and in men the site of lesion is the skin of the back and chest. Surface formations develop at a slow pace, gradually spreading by the skin.
- Nodal. It affects the chest, back and upper body.
- Acrolentiginous. This type is found on the palms of the hands or under the nails on the legs and hands.
- Lentyginous (Hutchinson's malignant freckle). It develops against the background of a pigment spot (mole). According to statistics, this form is more prone to the elderly female. Localization - skin, exposed to constant sun exposure. Most often, this is the face. Characterized by horizontal, slow growth and has the most favorable prognosis.
- Achromatic (non-pigmented). The rarest type of melanoma.

Skin cancer can affect the eyes, nose, mouth, lungs, rectum, etc. Therefore, there is a so-called classification of other melanomas, which includes:

- retinal melanoma;
- lentiginous melanoma of mucous membranes;
- malignant soft tissue melanoma.

Also, there is the concept of progressive melanoma. In this case, the cancer cells spread from their original site to other parts of the body, causing another tumor called secondary or metastatic cancer. The spread occurs in remote areas of the skin or affects the digestive tract, CNS and respiratory system.

Sometimes malignant melanoma occurs even many years after the initial removal of the initial formation.

Etiology of melanoma

The main causes of melanoma are based on two factors: uncontrolled exposure to solar radiation or artificial ultraviolet radiation through the use of solarium. Excessive enthusiasm for beach tanning or exposure to UV lamps entails a violation of the DNA structure of skin cells and increases the likelihood of cancer.

Pathogenesis of skin melanoma

The stages of the disease depend on the stage of melanoma and the degree of its prevalence. The depth of penetration of the primary tumor is measured in millimeters and determined by the methods of Breslow and Clark, which are based on the depth of penetration of cancer cells.

Medicine shares the development of melanoma at the stage (according to Breslow):

- I - formation occurs only in the outer layers of the skin (in the epidermis, to the basement membrane; thickness less than 2 mm).
- II - the tumor is found in the outer layers of the skin (thickness greater than 2 mm; may be characterized by the presence of an ulcer).
- III - the cancerous process extends to the lymph nodes near the site of the lesion and/or extends beyond the primary tumor site (the boundary between the papillary and reticular layers of the dermis).
- IV - tumor cells appear in the reticular layer of the dermis, germinate into fat tissue, metastases spread throughout the body, with selective damage to organs.

The division into microstadia according to Clark includes a thin, intermediate and thick (deep) form of invasion. Predictions vary based on existing stages of melanoma.

As the diagnosis and treatment occurred in the initial stages of the development of the disease (I, II), the prognosis is excellent and amounts to 98.2% survival. Stage III leaves life chances within 61.7%. Stage IV (especially with metastasis) are characterized by a rapidly progressive and fatal course. As a result, less than 10% survive for 5 years, and most patients expect death a year after diagnosis.

Clinical manifestations of melanoma

Most types of malignant melanoma begin with skin changes or with the appearance of a new mole. Also, the danger is the existing birthmark, which has changed its shape.

Signs of melanoma that should be noted when testing moles:

- geometry - an asymmetric mole in which one half is not equal to the other, may be a symptom of melanoma;
- border - a mole in which the contour is not rounded, clarity disappears;
- color is uneven and consists of several shades;
- diameter exceeds 5 mm.

Itching, scabies or bleeding are additional symptoms of melanoma. They are less common, but they cannot be ignored.

Treatment of melanoma

The early degree of the disease is characterized by a melanoma thickness of less than 1 mm. There are no signs that increase the risk of recurrence, such as an open wound or multiple mitosis. Removal of melanoma captures an area with a diameter of 1 cm.

Treatment of stage I and II melanoma. In the event that a cancerous tumor is diagnosed at a depth of penetration of more than 1 mm, a biopsy of the lymph nodes will be performed. If cancer cells are not found in them, a local operation will solve the problem.

If a lesion of regional lymph nodes is detected, this means that stage III has begun, which requires a more extensive operation. In the treatment of stage III melanoma, patients are offered auxiliary immunological therapy.

Actions at stage IV, when the focus of the disease spreads to other systems of the body with the appearance of metastases, requires a combination of surgical intervention and other methods. The treatment process for melanoma will depend on the site of the lesion, the general state of health and previous ways of influencing the tumor. Biochemical and immunological therapy are the most common methods of solving the problem. Radiation therapy helps control the symptoms of the disease if it has spread to the CNS, digestive tract or respiratory system.

As for surgery, it is performed in the area where the tumor is detected. After a biopsy confirming the diagnosis, a large local resection occurs. The surgeon necessarily removes a small part of the tissue, which seems normal in the area surrounding the tumor. This preventive action ensures that no cancer cells remain. This reduces the risk of melanoma recurrence.

Stages of skin cancer

The stage of cancer characterizes the severity of the disease. Separate classifications are distinguished for melanoma and non-melanoma types of skin cancer.

Table 1.1

Stages of melanoma

Stage	Characteristic
1	2
0	Applies only to the upper layers of the skin
1	Does not apply to healthy tissue, has a low risk of complications and can be surgically removed
2	Melanoma with an increased risk of recurrence (symptoms confirming the spread of cancer in the body may not be present)
3	Affects nearby lymph nodes or areas of skin
4	Spreads to distant lymph nodes, skin, or internal organs

At the zero stage of non-melanoma ("white") cancer, only the upper layers of the skin are damaged, at the first - the upper and middle layers. The second stage of pathology is characterized by damage to the nerves or deeper layers of the skin. When moving to the third stage, the cancer spreads to the lymph nodes. In the fourth stage, cancer cells affect other parts of the body and organs (in particular, the lungs, liver or brain).

Signs and symptoms of rarer skin cancers.

There are other, less common types of skin cancer, in particular:

- Kaposi's sarcoma. This rare form of skin cancer develops in the blood vessels of the skin and causes red or purple spots on the skin or mucous membranes.

  Kaposi's sarcoma is mostly found in people with weakened immune systems, such as those with AIDS or those taking immunosuppressive drugs, such as after an organ transplant. Young men living in Africa and older men of Italian or Eastern European Jewish descent also have an increased risk of Kaposi sarcoma.
- Merkel cell carcinoma. This type of cancer manifests as hard, shiny nodules appearing on or under the skin, as well as in hair follicles.

  Most often, Merkel cell carcinoma is found on the head, neck and trunk.
- Sebaceous gland carcinoma. This rare and aggressive cancer occurs in the sebaceous glands of the skin.

  Sebaceous gland carcinoma usually looks like hard, painless nodules. It can appear anywhere, but most often - on the eyelid, where it is often mistaken for other diseases of the eyelids.

1.2. Worldwide spread of this disease

June 13 marks European Skin Cancer Prevention Day. This disease is one of the most curable types of cancer. If it is diagnosed in time, 95% of cases can be cured. Despite this, the incidence of skin cancer has increased in recent decades, especially among young people. In particular, among women. This may be due to the fact that it is women who are most eager to sunbathe.[4]

Figures and facts [5] :

— Half of all tumors detected in the world are skin cancer.
— Since the 1970s, cases of skin cancer have increased compared to all other cancers combined.
— Skin cancer is more elusive than other types of oncology - after all, it becomes noticeable only 20 years after excessive exposure to sunlight or ultraviolet (UV) radiation.
— Since 80% of cases of sun damage occur before the age of 18, childhood education and protection are necessary to prevent future cases.
— In 2021, 11100 cases of skin cancer were detected in Ukraine and 465 deaths from this form of cancer were recorded.
— The indicator of the disease in the Zhytomyr region is 32.5 per 100 thousand (the world indicator is 16.1). The mortality rate from skin cancer in the region is 1.5 per 100 thousand (world figure -0.5).
— In 2022, 432 cases of skin cancer were recorded in the Zhytomyr region, 12 patients died.

Causes of skin cancer [5] :

— The main reason for the development of any form of primary skin oncology is the negative effect on the epidermis of ultraviolet rays. This includes both excessive solar insolation and abuse of trips to the solarium.
— The most dangerous type of cancer - melanoma - can develop from moles or age spots in 30% of cases.
— It is important to observe the existing nevi (pigment formations) on the body. If you notice that the birthmark or pigment spot has changed in size or color (increased and turned dark, began to bleed, itch or peel), their edges and shape have become uneven, ulcers have appeared - immediately consult a dermatologist to exclude the diagnosis of oncology.

Risk factors [5] :

- Excessive exposure to UV rays (UV rays) - visiting tanning beds, sunburn without appropriate sun protection.
- Previously received skin burns.
- Stay in direct sunlight from 11 to 16 hours of the day, when solar activity is highest.
- A large number of dysplastic nevi (flat moles or barely towering moles with uneven edges, painted in brown or black tones).
- Regular mechanical trauma of moles, age spots, scars, scars in the same place.
- Living in southern regions and regions where solar activity remains high all year round.
- Reduced immunity - for example, due to any chronic or recently transferred diseases.

Risk groups [5]:

- People with fair skin, which is more prone to sunburn due to insufficient production of the protective pigment melanin.
- Patients previously diagnosed with cancer: repeated recurrence of the disease is possible in more than 40% of cases.
- The risk of oncology is also doubled if this disease occurs in the history of relatives.
- Representatives of professions that involve contact with harmful chemical and carcinogenic substances (arsenic, household chemicals, radioactive substances, coal, fuel oil, paraffin, etc.) or working outdoors in direct sunlight.
- People over the age of 50.

1.3. Diagnostic methods

Diagnosis of melanoma

At the stage of early detection of possible skin cancer, it is necessary to carefully study the moles for signs of the disease. It is important to examine all areas of the skin, including the scalp, body folds, the space between the fingers, feet, lumbar area. Independent visual inspection is recommended to repeat at least 1 times every six months, it is even better to contact a specialist who will conduct a professional examination.

Instrumental methods for diagnosing melanoma include:

- Dermatoscopy - examination of the skin with a special device. As a result, the degree of danger of the disease is determined, with the possibility of assessing the development of events. Dermatoscopy is a mandatory stage of identifying skin problems.
- Any suspicion of skin oncology requires a biopsy. Tissue sampling from the affected area with subsequent histology should confirm or deny the presence of an oncological problem.

To determine the stage of the process in the diagnosis of melanoma, the oncologist prescribes additional tests, such as: laboratory blood test, ultrasound, computed tomography and magnetic resonance imaging of the brain with IV contrast (to exclude secondary brain damage), etc.

Diagnosis of epithelioma

As noted, the epithelioma is the combined name of a whole group of formations formed from epithelial cells. There are no specific symptoms. Therefore, it is important to establish a differentiated diagnosis. This is necessary to exclude other skin diseases, in particular allergic, viral, infectious nature.

To identify the formation, determine its size, location, character, a visual and hardware examination of the patient is carried out. The following diagnostic methods are used:

- Dermatoscopy, which involves inspection of the skin under conditions of multiple enlargement.
- Ultrasound study to determine the anatomy, depth of skin pathology.
- At breakthrough of formation - bacterial sowing of excreted liquid.
- Biopsy with the following histology.
- If necessary, radiography and MRI.

From the results obtained, a clinical diagnosis is made. If the dermatologist is not sure of the benign nature of the formation, the patient may be advised to consult an oncologist.

Diagnosis of Basalioma

The probability of diagnosis is confirmed by microscopic examination of the neoplasm. 2 methods are used: histological and cytological. During the analysis, the strands are oval, round, fusiform. The histological picture will differ depending on the type of basal cell.

Important is the differential diagnosis with other skin pathologies: psoriasis, lupus erythematosus, melanoma, etc. Additionally, the patient donates blood and urine for analysis. If the tumor germinates in cartilage and bones, radiography, CT, MRI are prescribed. It is also necessary to undergo a biopsy, during which a piece of the tumor or all the tumors is taken and sent for cytology.

Dermatoscopy allows you to contactless determine the nature of the tumor. Dermatoscope increases the growth many times, so that the doctor examines its structure, inequality of boundaries, symmetry, level of danger. The accuracy of this method is more than 80%.

1.4. Rationale for using artificial intelligence to diagnose skin cancer

Skin cancer remains one of the most common cancers, and its timely diagnosis is critical for successful treatment. As seen in the previous section (1.2), the main diagnostic methods include dermatoscopy, biopsy, visual examination, ultrasound, CT and MRI. However, these methods have certain limitations:

- Subjectivity of visual assessment: Traditional diagnosis largely depends on the doctor's experience, which can lead to discrepancies in diagnoses.
- Invasiveness of biopsy: Although biopsy is the "gold standard," it is a traumatic procedure and may not always be performed in the early stages.
- Limited availability of specialists: In many regions there is a shortage of qualified dermatologists and oncologists.

— Difficulties of differential diagnosis: Many forms of skin cancer (eg, basal cell, melanoma, epithelioma) have similar clinical manifestations.

It is in this context that artificial intelligence offers innovative solutions that can complement or improve traditional diagnostic methods.

Improving dermatoscopy with AI

Modern deep learning systems can analyze dermatoscopic images with more than 90% accuracy. Algorithms are able to detect:

— Asymmetry of formations;

— Uneven contours;

— Color anomalies;

— Dynamics of change;

This is especially important for differentiation between benign nevi and melanoma in the early stages.

Non-invasive alternative to biopsy

AI systems analyzing confocal microscopy or OCT images can provide accurate diagnosis without the need for a biopsy at the initial stages of the examination**.**

Differential diagnostic support

AI is especially effective for distinguishing similar pathologies:

— Basalioma vs psoriasis;

— Melanoma vs dysplastic nevus;

— Epithelioma vs benign formations.

Prognostic models

Machine learning allows:

— Predict malignancy risk;

— Assess likelihood of relapse;

— Select individual surveillance strategies.

The integration of artificial intelligence into the diagnosis of skin cancer can overcome the main limitations of traditional methods. Particularly valuable is the combination of AI with dermatoscopy, which increases the accuracy of diagnosis in the early stages. The future development of these technologies promises to make the diagnosis of skin cancer more accessible, objective and effective.

1.5. Artificial neural network. Mathematical model artificial neuron

In modern science and technology, the concept of "artificial neural network" (SNM) has become synonymous with the concept of "intellectual systems," because it is these structures that underlie many achievements in artificial intelligence. Artificial neural networks are mathematical models that mimic the work of the human biological brain. Their task is to learn how to find patterns in the data and make decisions based on learning. The neural network consists of a large number of elementary units - neurons, which are combined into layers: input, hidden and output. Each neuron in the hidden layers performs a simple computational operation - a weighted sum of input signals passed through the activation function. It is this function that allows the network to solve nonlinear problems.

An artificial neuron is a mathematical model that performs calculations using the formula:

$$y = f(\sum_{i=1}^{n} w_i x_i + b),$$

Formula 1. Mathematical model of artificial neuron

where , x_i - input signals, w_i - weights (training parameters), b - displacement, f - activation function (for example , sigmoid, ReLU or tanh), y - neuron output.

The perceptron is the simplest model of an artificial neuron, which was proposed by Frank Rosenblatt in 1957. It mimics the work of a single biological neuron and is the basis for building more complex neural networks. [26]

The initial perceptron was created to process multiple binary inputs and produce one binary result (0 or 1).

The essence was that each input was assigned a certain weight, which determined its significance, and only when the weighted amount exceeded a given threshold, the system made a decision - yes or no (true/false, 1 or 0).

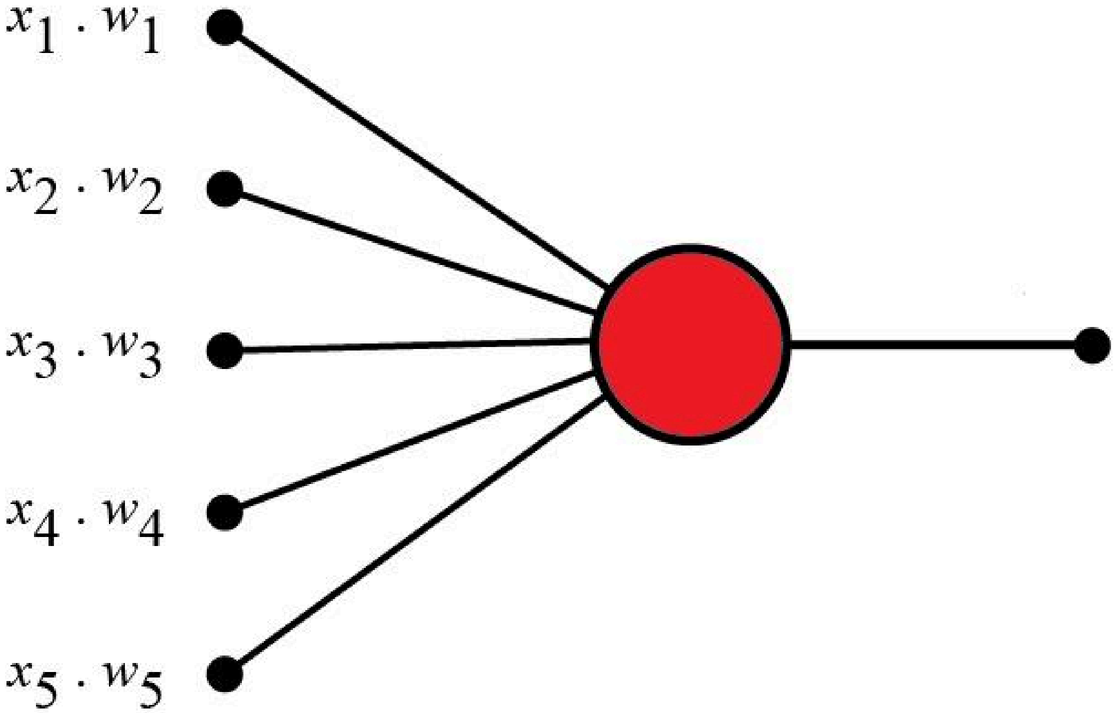

Fig. 1.4. Perceptron example [26]

The idea is that the neuron receives signals from previous layers, sums them up with certain weights, and then decides how "active" it should transmit the signal further. The basis of learning CNM is the backpropagation algorithm, which allows you to adjust the weights of neurons so that the network gradually reduces the error in its predictions. Thanks to this, the SNP is able not only to memorize data, but also to generalize - to draw conclusions even on the basis of new examples that it did not see during the training. Thus, an artificial neuron is the main "building unit," and an artificial neural network is a complex system of thousands or even millions of such neurons that work together to solve intellectual problems, in particular image classification, speech recognition, prediction, etc.

However, generative modeling - that is, the creation of new data based on the studied patterns - has become a separate direction for the development of artificial neural networks. In this context, special attention is drawn to Generative Adversarial

Networks (GAN), which combine two neural networks - a generator and a discriminator - competing with each other. It is this architecture that allows you to obtain high-quality synthetic images, and, as will be shown in the following sections, use the adversarial principle to solve diagnostic problems in medicine.

1.6. Justification for the use of generative adversarial networks. Classification

Generative Adversarial Networks (GAN) is one of the most famous breakthroughs in the field of artificial intelligence in recent decades. First introduced by Ian Goodfellow in 2014, [19] this architecture ushered in a new era in generative modeling, especially for images. In general, the GAN consists of two components - the generator and the discriminator, which compete with each other. Over time, many variations of this basic idea have appeared, each of which solves certain limitations or improves the quality of generation. This allows the GAN to be classified according to various criteria.

GAN variations :

- Classic (Vanilla) GAN. This is a basic architecture that works on the principle of competition between the generator and the discriminator. It is well suited for theoretical studies, but has limited stability and often suffers from the "mode collapse" problem. [19]
- Deep Convolutional GAN (DCGAN). An extension of the classical GAN, where convolutional and deconvolutionary layers are used instead of fully connected layers. This significantly improves the quality of the generated images and makes the architecture more stable when learning [20].
- Conditional GAN (cGAN). Adds a class label to the input noise, allowing the generator to create an image of a specific category. This is especially useful in tasks where you need to control what exactly is generated [21].
- Wasserstein GAN (WGAN). This type of GAN changes the loss function, replacing cross-entropy with Wasserstein distance, which makes learning much more stable. It is also important to introduce clipping scales or gradient penalty [22].

— StyleGAN i StyleGAN2. These are high-level architectures used to generate extremely realistic faces or complex objects. StyleGAN introduces style control at different generation levels (coarse → fine features), and StyleGAN2 eliminates artifacts from the first version [22].

As part of this work, Deep Revolutionary GAN (DCGAN) was used - a variation of the classical GAN, which is based on convolutional layers. This architecture is significantly more stable in training compared to Vanilla GAN, and also allows you to effectively work with images of skin lesions, while maintaining their spatial structure.

A feature of the implemented system is the rejection of generation as the main goal - in the final version of the work, the emphasis is on adapting the DCGAN discriminator for the task of binary classification of skin lesions (benign/malignant). This approach made it possible to take advantage of the architectural advantages of DCGAN (convolutions, stabilization through BatchNorm, LeakyReLU) to build a lightweight but effective classification model.

Another advantage of using the DCGAN discriminator as a classifier is that its original purpose - to distinguish real images from generated ones - has a similar nature to the task of classifying "healthy/pathological." With this transfer of the idea of adversarial into the context of classification allows you to build accurate, detail-sensitive models.

Taking into account the specifics of the task (a limited amount of data, visual complexity of skin lesions, the need for high sensitivity to malignant forms), DCGAN turned out to be the best choice. Its discriminator has been modified towards a full-fledged classifier and trained using class weights to compensate for the imbalance in the dataset. The calculation of exact metrics (accuracy, completeness, F1, AUC) for quantitative evaluation of results is also implemented.

Thus, the use of the DCGAN discriminator as a basis for classification allows combining the advantages of generative architecture with stability and accuracy in medical diagnosis tasks.

1.7. Generative adversarial network architecture.

A generative adversarial network (GAN) is a type of deep learning model capable of generating extremely realistic new data based on a training set. GAN was first introduced in 2014 by Ian Goodfellow and colleagues. [19] The GAN model works on the principle of competition between two artificial neural networks:

- **Generator (G):** responsible for creating artificial data that is as close as possible to the real ones.
- **Discriminator (D):** Responsible for distinguishing between real data and fake data created by the Generator.

These two networks learn simultaneously in a continuous process, where the Generator tries to deceive the Discriminator, and the Discriminator tries to recognize exactly where the real data is and where the artificial data is. Over time, the Generator improves its ability to create increasingly realistic data. GAN has powerful applications in various fields, in particular: image generation, image recovery, creation of artistic content, improvement of medical data, as well as in Deepfake technology - a method of modifying images and videos.

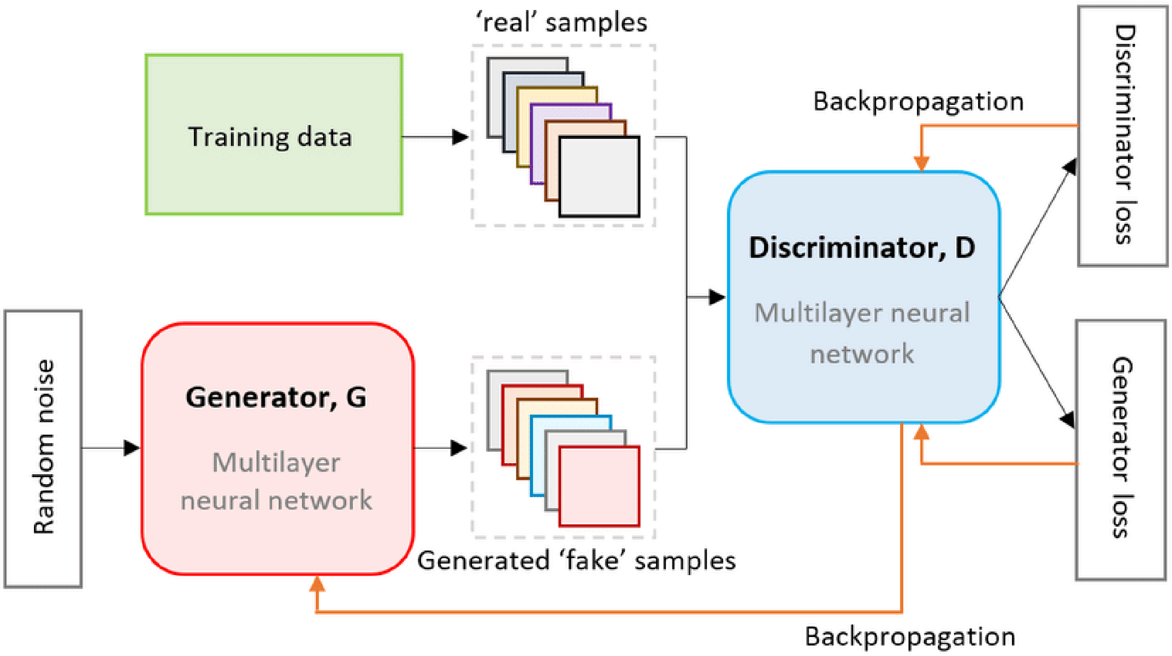

Fig. 1.5. GAN architecture [15]

GAN structure

The Generative Adversarial Network (GAN) operates on the basis of an adversarial mechanism between two deep learning models: Generator and Discriminator. These two models continuously interact to create new data with a high level of realism, making GAN one of the most powerful artificial intelligence technologies in the field of deep learning.

Generator (G)

The generator acts as a "forger," trying to create fake data that looks as realistic as possible. It receives a random vector, usually a noise vector (z), taken from a certain probabilistic distribution, for example, a normal (Gaussian) distribution. Then, using an artificial neural network, the Generator converts this input into a new sample, similar to training data.

Initially, the samples created by the Generator are of very poor quality and are easily recognized by the Discriminator. However, over time, the Generator learns to create more realistic patterns to deceive the Discriminator.

During training, the generator does not receive direct feedback on the quality of images, but learns only how well it managed to deceive the discriminator. That is why the generator loss function is based on the probability with which the discriminator classifies the generated images as true:

$$J_G = -\frac{1}{m}\sum_{i=1}^{m} logD(G(z_i)),$$

Formula 2. GAN generator loss function

where , J_G - measures how well the generator is cheating the discriminator, m - number of examples in the mini-batch, z_i - random noise (for example i), $G(z_i)$ - is a generated sample from random noise, $D(G(z_i))$ - probability that the discriminator will take the generated image for the true,

The Generator architecture depends on the type of output required. If Generator is used to create images, deep convolutional neural networks (DCNNs) are usually used to ensure the clarity and realism of images. Instead, if the GAN is used for text or audio processing, the Generator can use recurrent neural networks (RNNs) to simulate serial data.

Common Generator architectures:

- **Fully Connected Neural Networks (FCNN):** Basic neural network architecture.
- **Deep Revolutionary Neural Networks (DCNN):** Use convolutional layers to generate sharper images.

Discriminator (D)

The discriminator acts as a "judge" responsible for distinguishing between real data from the training set and fake data generated by the Generator. He receives a sample at the input and, using a neural network, evaluates whether this sample belongs to real data, or was created by the Generator.

The original Discriminator value is a probability in the range of 0 to 1, where a value close to 1 indicates a high probability that the data is real and a value close to 0 indicates that the data is fake.

The discriminator tries to minimize these losses:

$$J_D = -\frac{1}{m}\sum_{i=1}^{m} logD(x_i) - \frac{1}{m}\sum_{i=1}^{m} log(1 - D(G(z_i))),$$

Formula 3. GAN discriminator loss function

where , J_D - determines how well the discriminator classifies real and fake samples, x_i - real sample from the dataset, $G(z_i)$ - fake pattern generated by the generator, $D(x_i)$ - the probability that the discriminator assigns because x_i is real . $D(G(z_i))$ - the probability that the discriminator assigns because the fake pattern is real.

The discriminator continuously learns to accurately distinguish between real and fake data. If he manages to detect a fake, the Generator must improve its generation methods in order to better deceive him. Just like the Generator, the Discriminator can use convolutional neural networks (CNNs) for image processing or recurrent neural networks (RNNs) for processing serial data such as speech or text.

Common Discriminator architectures:

- **Revolutionary Neural Networks (CNN):** Suitable for image processing.
- **Recurrent Neural Networks (RNN):** Used to process real-time data such as speech and text.

CHAPTER 2.
DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORK

In recent years, artificial intelligence (AI) has made significant progress, especially in the fields of data generation and image processing. One of the most prominent technologies in this field is generative adversarial network (GAN), which is considered revolutionary in the creative possibilities of AI. Due to its unique structure, GAN is able to generate images, video, audio and simulated data with an impressive level of realism.

2.1. DCGAN architecture. Principle, features

The DCGAN (Deep Revolutionary Generative Adversarial Network) architecture was proposed by Redford et al in 2016 as an improved version of the classic generative adversarial networks (GANs). Its key difference is the use of convolutional and transposed convolutional layers instead of fully connected ones, which significantly improves the quality of work with images due to the preservation of their spatial structure [20].

In general, the DCGAN architecture consists of two parts: a generator and a discriminator. The generator begins its work with random noise - a vector of 100 numbers generated, for example, from a normal distribution. This vector passes through several layers of "transposed convolution," which gradually increase its dimension and form an image from it. Each layer uses Batch Normalization and ReLU, and the last layer is Tanh, which normalizes the original image to the range [-1, 1] [20,16].

In the process of learning, the generator tries to create images that will be taken by the discriminator for the real ones. Its loss function is specified in the previous section (see Formula 2).

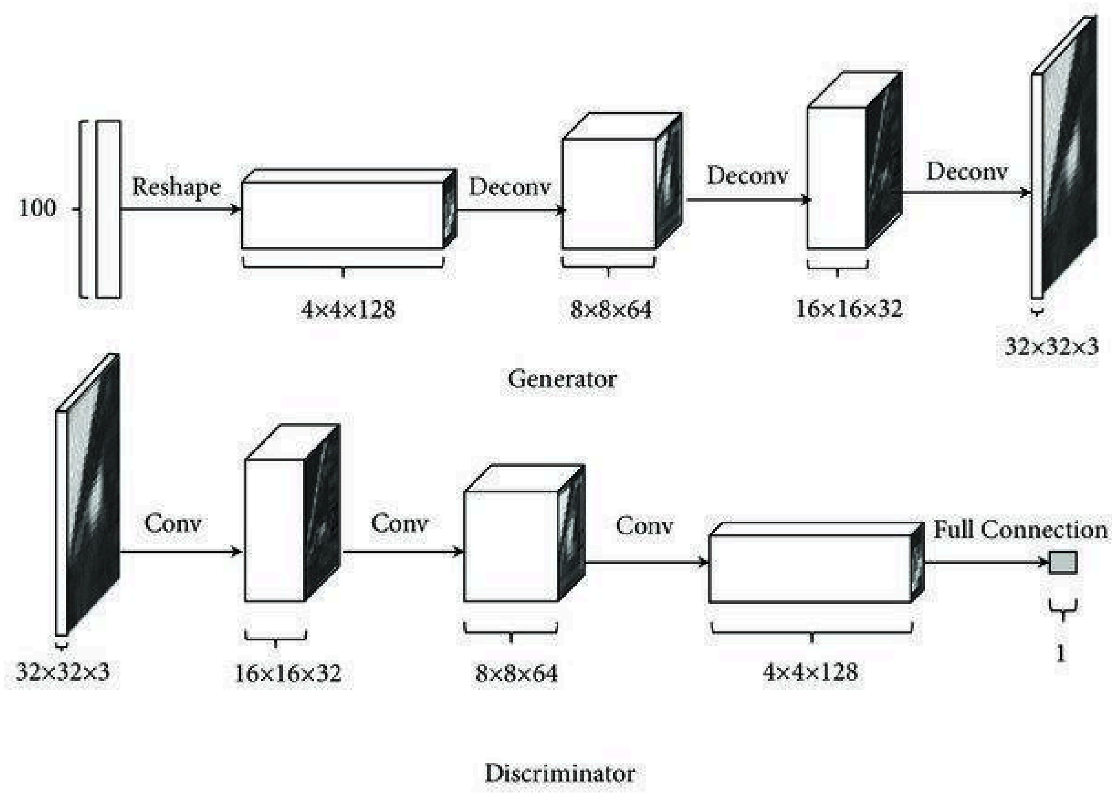

Fig. 2.1. DCGAN Architecture [24]

The discriminator, in turn, acts as a critic. Its task is to distinguish the real image from the dataset from the generated one. It is built on conventional convolutional layers using LeakyReLU activation, which avoids the problem of fading gradients. The discriminator also uses BatchNorm (except for the first layer), and the output uses the Sigmoid or Softmax activation function, which gives the probability that the image is true [20].

In my system, this basic structure was adapted: the final layer of the discriminator was replaced by a fully connected network, which allows us to classify the image not only according to the "real/fake" criterion, but also according to the diagnostic criterion - benign or malignant skin lesion. Thus, the discriminator performs a dual function: during training, it competes with the generator, and after completion, it works as an effective binary classifier. This approach allows you to unify the architecture, reduce the number of system parameters and improve its consistency.

In turn, the discriminator must learn to distinguish between real and fake images. Its loss function combines both cases (see Formula 3).

The main architectural principles of DCGAN, which were formulated in [20]:

- No pooling - convolutions with stride > 1 are used instead;
- The generator uses transposed convolution instead of upsampling;
- The discriminator uses ordinary convolutions from stride 2;
- All layers except the last in the generator and the first in the discriminator use BatchNorm;
- ReLU - in the generator, LeakyReLU - in the discriminator.

This approach provides significantly higher learning stability and better image quality compared to classical GANs. For example, in classical GANs, the problem of "mode collapse" often arises when the generator creates only a few similar images. DCGAN addresses this problem in part through deeper structure and architectural constraints. [16,18]

For example, the generator and discriminator architecture that I implemented in my system for generating images of skin lesions (based on articles [18,19]) includes up to five convolutional or deconvolutional layers with filters 4 × 4, stride 2 and padding 1. It is this configuration that allows you to effectively reduce or increase the dimension of images without losing important features.

In the table below (see Table 2.1) I gave a comparison of GAN and DCGAN by several criteria. It should be inserted into the text after the paragraph, which discusses the advantages of DCGAN over classic GAN. It is also advisable to add a DCGAN architecture scheme (for example, with [16] or my own), after describing the generator and discriminator.

Table 2.1

Comparison of GAN and DCGAN

Criterion	GAN (classic)	DCGAN
Layers type	fully connected layers (Dense)	Convolutional(Conv / TransposedConv)
Working with images	Обмежено	Optimized for images
Image quality	Rough, bluri	Clear, realistic
Stability of training	Unstable	More stable
Depth of network	Small	Deeper
BatchNorm	Необов'язково	Required except for individual layers
Activation	ReLU (often)	ReLU in Generator, LeakyReLU in Discriminator
Processing spatial characteristics	Ignore	Takes into account (spatial structure)

2.2. Review of scientific papers on DCGAN

Review of the scientific article: "Skin Lesion Synthesis and Classification Using an Improved DCGAN Classifier "[17].

Written by Kavita Behara, Ernest Bhero and John Terghil Agee.

In the current situation of the development of digital medicine, the issue of early diagnosis of skin cancer continues to be very relevant. Although there are dermatoscopic methods of searching for neoplasms, the effectiveness of diagnosis is very dependent on the qualifications of the doctor. The article discusses the method that is obliged to automate this process when using deep neural networks, in particular the DCGAN model.

The authors of the article Kavita Behara, Ernest Bhero and John Terhile Agee proposed an improved version of DCGAN for the synthesis of images of skin lesions, as well as the classification of these images into benign and malignant. The study is based on the well-known ISIC 2017 dataset, containing dermatoscopic images of various types of skin neoplasms.

The article notes the most important issue - the limitations of the doctor-annotated data for the training of deep navchannya._issue networks is especially acute for tasks related to a rare pathology, for example, melanoma. The authors proposed to play into this hands by using a generative adversarial network (GAN) that can create realistic synthetic differences.

The model consists of two of its components - the generator and the discriminator. The generator causes fake images that need to be like real photographic images of dermatoscopes, and the discriminator learned to recognize between them the present or not. In a simplified version of DCGAN, the authors used five de/convolutional layers instead of the usual four and used the activation functions ReLU (in the generator) and LeakyReLU (in the discriminator), and also changed the structure of the original layers for internal classification.

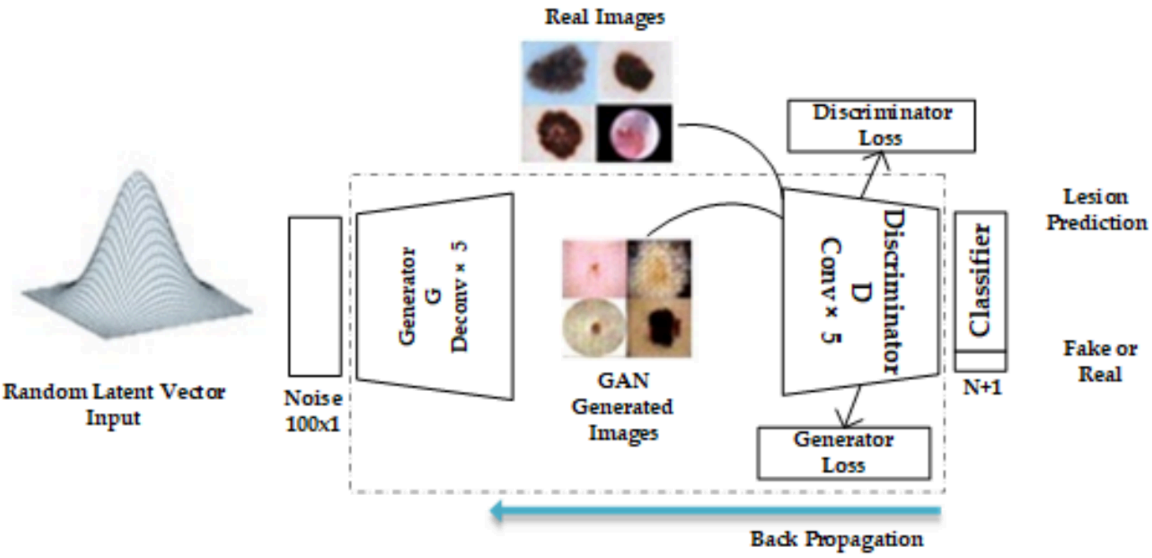

Fig. 2.2. Improved DCGAN model architecture [17]

One of the features of this model is the use of special methods of preprocessing images: scaling, improving contrast, filtering noise, converting color space and increasing the clarity of images. Thanks to these methods, it was possible to significantly improve network training and increase the quality of synthesized images.

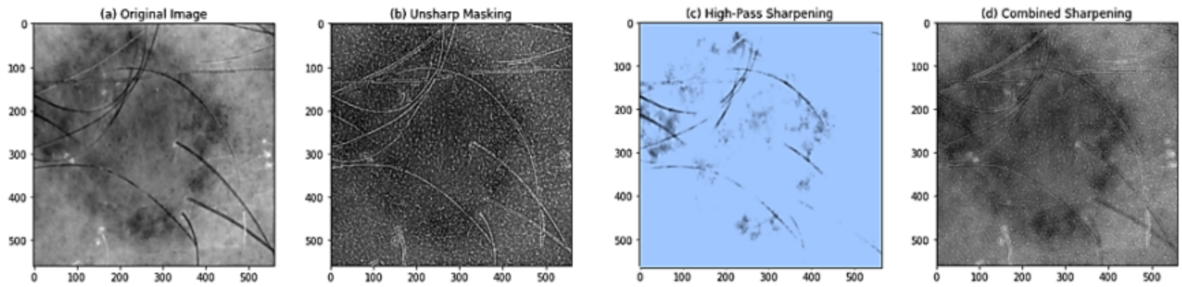

Fig. 2.3. Example of image processing - before and after applying filters [17]

The study also describes a procedure for training a model based on the adversarial principle (minimax): the discriminator tries to distinguish real images from synthetic ones, while the generator tries to deceive the discriminator. For this, the loss function with cross entropy was used. It is important that the discriminator in this model also acts as a classifier, determining which category the image belongs to - benign or malignant.

$$min_G max_D V(G, D) = E_{x\sim Pdata(x)}[log(x)] + E_{x\sim Pz(z)}[log(1 - D(G(z)))],$$

Formula 4. GAN loss function [17]

where , G - generator, D - discriminator , $E_{x\sim Pdata(x)}[log(x)]$ - mathematical expectation (mean) for true images x, taken from the real distribution $Pdata(x)$, x - real images Pdata(x)- real data distribution, $E_{x\sim Pz(z)}[log(1 - D(G(z)))]$ - average value for generated images generated by the generator G from random noise z, taken from distribution $Pz(z)$ (for example , normal), z - random noise, Pz(z) - random noise distribution, 1-D(G(z))- probability that the discriminator correctly recognizes the fake, D(G(z)) — probability that the discriminator considers the fake image to be genuine, G(z) — fake image , E - mean or expected value.

Training of the model was carried out using the SGD optimizer with momentum, with a fixed learning rate of 0.01, which, according to the authors, avoided instability during convergence, which is a typical problem for GAN models.

The results of the study look impressive: the classification accuracy reached 99.38%, which significantly exceeds the performance of the classic CNN models. In addition, the model has demonstrated high accuracy, recall, precision, F1-miru and Balanced Accuracy Score (BAS), which allows us to conclude that it is suitable for use in clinical settings.

Table 2.2

Comparison of metrics between Improved DCGAN and other models [17]

Techniques	Dataset	Observation	Accuracy(%)
1	2	3	4
Pix2Pix GAN	ISIC 2017	Image-to-image conversion was performed by binary classification using a combination of semantic and instance mapping.	84.7
GAN with Raman Spectroscopy	Raman Spectroscopy	The authors created a data extension module that uses GAN to generate remote sensing (RS) data corresponding to the training data classes.	92
cGAN and WGAN	ISIC 2016	The authors proposed a categorical generative-adversarial network that operates in both uncontrolled and semi-controllable modes to automatically learn how to present the signs of dermoscopic images.	81
DDGAN	ISIC2017	Synthesis of high-quality images of skin lesions has been	72

Table 2.3 (continued)

1	2	3	4
		demonstrated. However, synthetic images visually had a low contrast.	
ACGAN, CycleGAN and Path-	ISIC 2019	Studies have shown that random noise and image conversion can create high-quality images that	85.6
Rank-Filter		seem real to the untrained eye. However, these images did not improve the efficiency of the classifier.	
DCGAN	ISIC 2016–2021	A Turing test was performed on the generated images, for a total of 7,000 images.	58.72
GAN	ISIC 2018	A classifier based on GAN was created by fine-tuning the existing deep neural architecture.	86.1
DCGAN	ISIC	The two-way filter improved feature recognition and retrieval during training. Fine tuning the Deep Convolutional Generative-Rival Network (DCGAN) has increased its efficiency. Optimization allowed us to choose the best combinations	93.5

Table 2.3 (continued)

1	2	3	4
		of network and hyperparameters. Fine-tuning hyperparameters requires GPU time and power.	
styleGAN	ISIC 2018	The generator and discriminator were modified to synthesize high-quality images of skin lesions by modifying the generator style control and input	95.2
		noise structure. Transfer learning on a pre-trained deep neural network classifies images. Finally, synthetic images of skin lesions based on the GAN style are added to the training set to improve the efficiency of the classifier.	
DGAN	PH2 SD-198 Interactive Atlas of Dermoscopy DermNet	A multi-class technique was used to address the class imbalance in the dataset. Improving the stability of the DGAN model during training has become one of the main problems in the development process.	91.1

Table 2.3 (continued)

1	2	3	4
SLA-StyleGAN	ISIC 2019	The proposed approach surpasses GAN and StyleGAN in the main parameters of quantification and quickly generates high-quality images of skin lesions. It restores the generator and discriminator structures of StyleGAN. Disadvantage: two skin lesions in one image can complicate classification and increase the risk of misdiagnosis.	93.64

In conclusion, this article not only includes an effective mechanism for solving the problem of data shortage through the generation of synthetic images, but also emphasizes the prospects of using deep learning in medical diagnostic medicine. The introduction of this type of system into clinical practice, on the other hand, will involve additional studies on more representative samples.

Given all of the above, this work can be used as a solid basis for creating an intelligent diagnostic system.

Review of the scientific article: "Exploring deep convolutional generative adversarial networks (DCGAN) in biometric systems: a survey study "[18] Written by John Jenkins, Kaushik Roy.

In today's digital world, biometric authentication systems play a leading role in securing access to information resources. But with the advent of generative methods, in particular deep generative adversarial networks (GAN), the possibility arose of creating artificial biometric data that can deceive such systems. A review article by

John Jenkins and Kaushik Roy (2024) examines the use of DCGAN architecture in biometric systems and its impact on cybersecurity.

The authors begin with a general introduction to the context of deep learning, explaining that generative adversarial networks consist of two models - a generator and a discriminator - that learn as a zero-sum game: the generator creates images, and the discriminator tries to determine whether they are true. DCGAN is a GAN architecture modified specifically for image processing. It combines GAN with convolutional neural networks (CNNs), which ensures higher quality of generated images and stability during training.

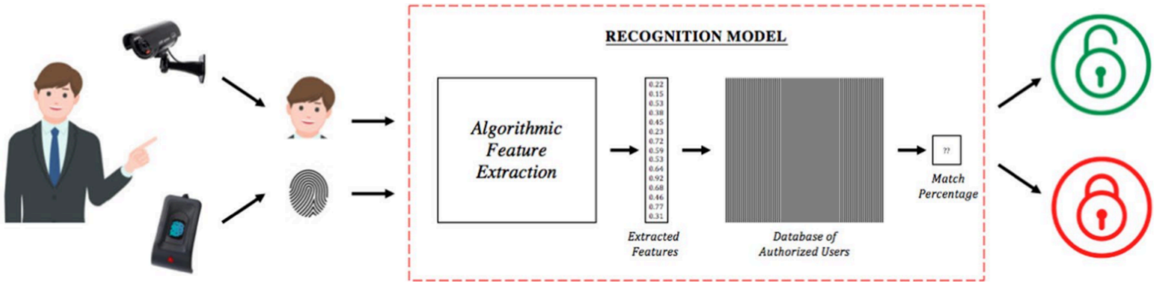

Fig. 2.4. Diagram of a typical biometric system [18]

The DCGAN architecture is based on replacing pooling layers with strided convolution and fractional convolutions for scaling. The generator in DCGAN receives a 100-dimensional random noise vector at the input, which passes through several convolutional layers with ReLU activation and normalization. The last layer uses the tanh function to bring the output values to the range [-1, 1]. The discriminator, on the contrary, performs the opposite action - reduces the dimension through strided-convolution, applies LeakyReLU and derives the probability of authenticity of the image.

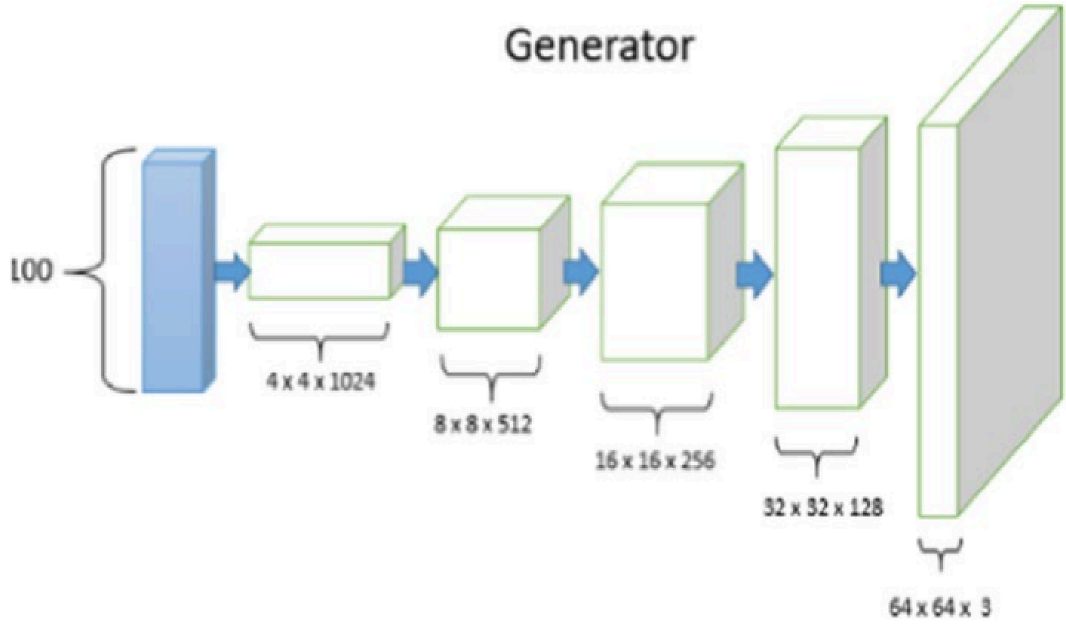

Fig. 2.5. DCGAN generator architecture [18]

Illustration of the DCGAN generator model with four fractional shear convolutions. The first layer of the model receives a 100-dimensional uniform noise distribution, and the final layer of the model generates a synthetic image of 64 × 64 pixels

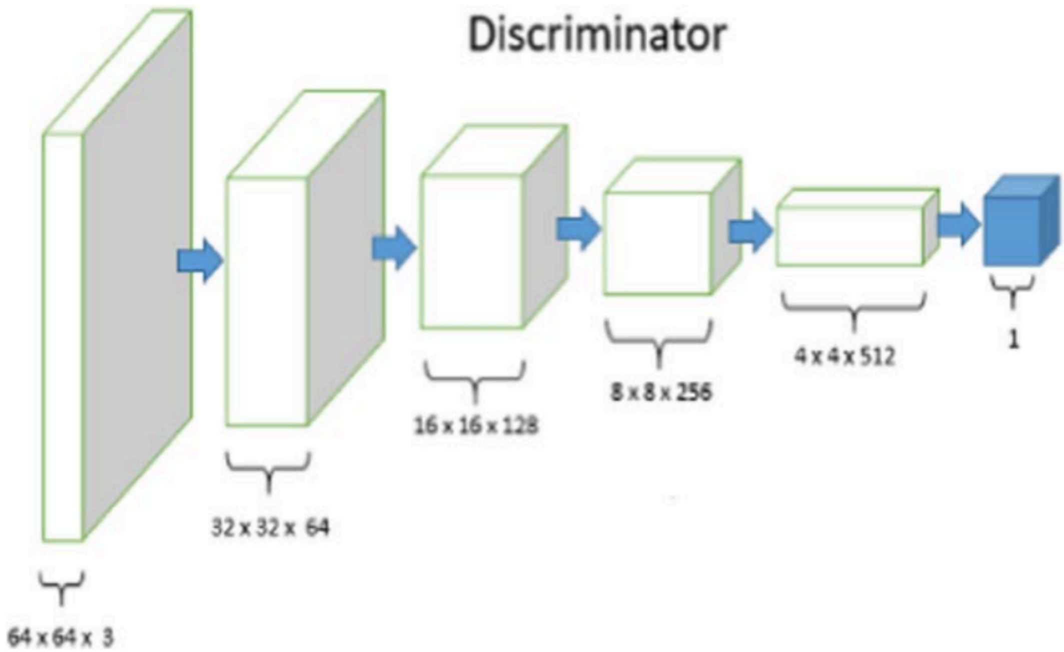

Fig. 2.6. DCGAN Discriminator Architecture [18]

Illustration of the DCGAN Discriminator Model with Four Shift Convolutions [see Fig. 9]. The first layer of the model takes the synthetic image as an input, and the final layer produces one neuron - a probabilistic estimate that the input image is true Special attention is paid to the problems of DCGAN training: gradient disappearance, mode collapse, unstable convergence. To improve learning, the Adam optimizer and the loss function - binary cross-entropy are used.

The main part of the article is a large-scale review of works where DCGAN is applied to various biometric modalities: face, iris, fingerprints, palms. The article explores two main areas:

1. Generation of high-quality biometric images:

- DCGAN is used to create fake faces (CelebA), fingerprints, irises of the eye that do not differ from the real ones.
- Quality is evaluated using SSIM, FID, Inception Score and other metrics.
- For example, in Liu et al. (2021) fake faces were generated with FID ≈ 49.3 and IS = 1.074 - enough to train other models.

Table 2.4

Comparison of DCGAN models for biometrics generation [18]

Year	**Authors**	**Model Description**	**Biometrics**	**Datasets**	**Results**
1	2	3	4	5	6
2019	Choi et al.	DCGAN using Heming distance, histogram correlation and IoU	Fingerprints	–	The generated data is similar to the real data, improve the data of fake

Table 2.4 (Continued)

1	2	3	4	5	6
					fingerprints
2019	Liu et al.	DCGAN	Face	CelebA	Modeling virtual faces with high similarity
2020	Xiangli et al.	RealnessGAN (на базі DCGAN)	Face	CelebA, FFHQ	High FID and SWD, more stable learning
2021	Shariff et al.	DCGAN	Face	CelebA	SSIM showed similarity to real images
2021	Liu et al.	DCGAN з фокусом на низькі ресурси	Face	CelebA	The balance of quality and time is achieved in 4 epochs
2021	Barni et al.	De-ID методом на основі DCGAN	Iris of the eye	CASIA-Iris V4, IITD-IrisV1	Good deidentification with preservation of structure

1	2	3	4	5	6
2021	Vincent et al.	DCGAN with improved loss function	Fingerprints	Anguli	High SSIM and FID, clear image structure
2022	Bamoriya et al.	DSB-GAN (CAE + DCGAN)	Prints, rainbow, palm	PolyU, IITD	High similarity and variability by MS-SSIM та FID
2023	Canan et al.	DCGAN	Face	CelebA	Quality grows with increasing eras and data
2023	Kumar et al.	DCGAN	Face	CelebA	High Inception Score i FID
2023	Kapalavai et al.	DCGAN + ESRGAN	Face	CelebA	Average SSIM = 0.31, quality confirmed

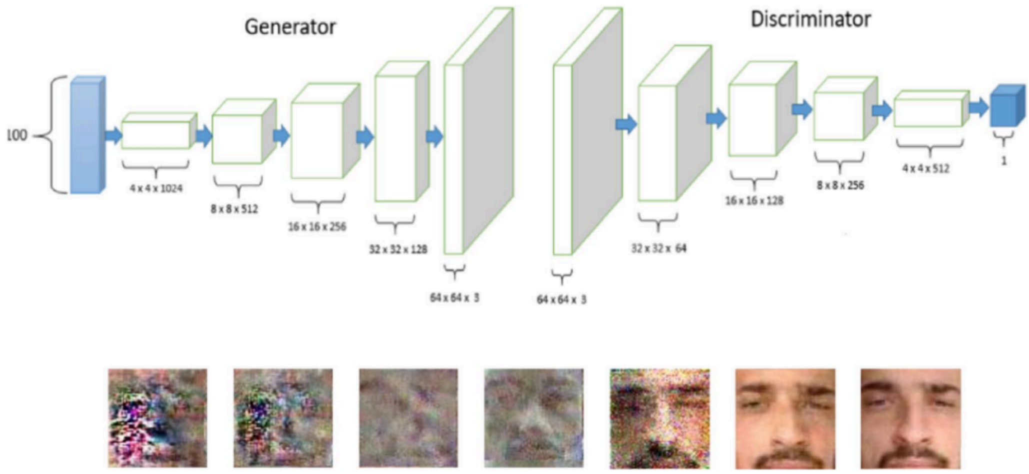

Fig. 2.7. The process of evolution of synthetic facial images [18]

2. Improvement of biometric systems:

- DCGAN is used as a method of augmentation of data, imitation of attacks (presentation attack), or for training on fakes (adversarial training).
- For example, iDCGAN was used to generate fake irises that bypassed the state-of-the-art DESIST protection system (efficiency fell by 14%).
- Other studies demonstrate how fake data from DCGAN helps make biometric models more sustainable.

Table 2.5

Application of DCGAN in improving biometric systems [18]

Year	Authors	Model description	Biometric	Dataset	Result
1	2	3	4	5	6
2017	Kohli et al.	iDCGAN + DESIST (attack detection)	Iris of the eye	IIITD, IIT Delhi, MultiSensor	DCGAN Generate hard to detect

Table 2.5 (Continued)

1	2	3	4	5	6
					images DESIST
2018	Wang et al.	DCGAN for augumentation + Xception for recognition	Palm	CASIA, IIT Delhi	High quality, EER: 0.37% i 1.52%
2019	Gupta et al.	AnoGAN for liveness detection	Palm	Own database	AUC = 96.8%, HTER = 3%
2019	Engelsma et al.	Classmate classifier on discriminator DCGAN	Fingerprints	Own database	Higher TDR (49.8%) then base model
2020	Yang et al.	FV-GAN (based on DCGAN i CycleGAN)	Veins of fingers	THU-FVFD, SDU	Improved recognition accuracy and efficiency
2020	Xuan et al.	DCGAN/WGAN-GP/P	Face	CelebA-HQ	Improved generalizati

Table 2.5 (Continued)

1	2	3	4	5	6
		GGAN для генерації			on of CNN models
2020	Jenkins et al.	DCGAN + GEFE for analysis of eye angles	Periocular	BIPLab	Detect attacks over important FEs
2022	Lv et al.	DCGAN + CNN з ELBP	Face	CelebA	Extended dataset, improved accuracy
2022	Siddiqui et al.	DCGAN + змінений VGGNet	Iris of the eye, periocular	MICHE-I, VISOB, UBI-Pr	VGGNet outperforms AlexNet and SpoofNet
2023	Ammar et al.	DCGAN + FaceNet	Face	LFW, ChokePoint	Better then LBP, PCA, and even VGG-16
2023	Wang et al.	DCGAN for FA attch	Palm	PolyU	Generated images are accepted as real

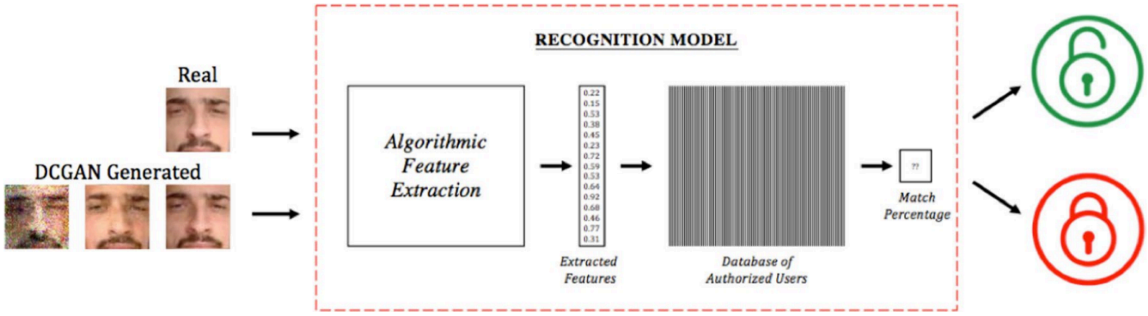

Fig. 2.8. An example of using fake data to train a recognition system [18]

In a general conclusion, the authors argue that DCGAN is a simple, stable and efficient architecture that is actively used in biometrics. At the same time, they warn that the development of such models can be used by cybercriminals, so further research is needed on protection systems against fake biometric samples.

This review is an important source for the analysis of the architectural features of DCGAN, their adaptation to biometric systems and role in modern security problems, and will be useful material for further research in a thesis on the classification of skin diseases.

Review of the scientific article: "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks "[20].

Written by Alec Radford, Luke Meltz , Soumith Chintala.

In the world of computer vision and deep learning, the biggest trend is not only to improve the quality of image classification, but also the ability of models to learn from unmarked data. This is exactly what the work of Alec Radford, Luke Metz and Soumit Chintala is devoted to, in which the Deep Revolutionary GAN (DCGAN) architecture is proposed - a variation of generative-adversarial networks that combines the power of convolutional neural networks and the potential of uncontrolled learning.

The authors begin by looking at the problem: despite CNN's advances in the task of supervised learning, unmanaged learning remains less researched. GANs proposed by Goodfellow in 2014 provide the generation of new images from random noise, creating photogenic copies based on real samples. But classic GANs were unstable when learning. In response, a group of researchers proposes a modified architecture - DCGAN, which provides stable learning of deep generative models on real images and at the same time use the discriminator as a powerful feature extractor.

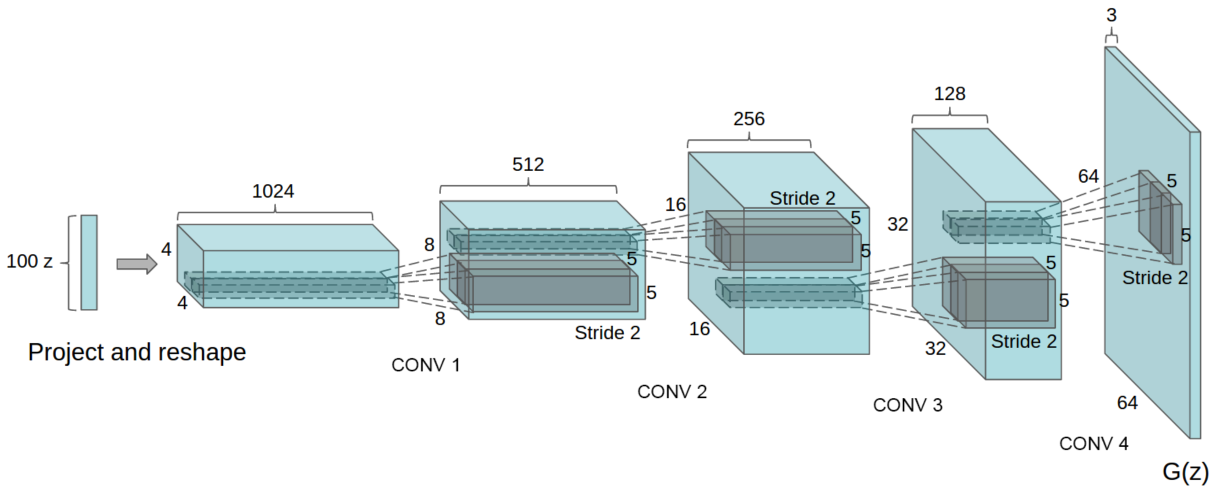

Fig. 2.9. DCGAN architecture [20]

The diagram shows how the 100-dimensional noise vector Z passes through a cascade of fractional-strided convolutions, increasing the spatial dimensions and turning into an image of 64 × 64 pixels. The generator uses ReLU for all layers except the original one - where tanh is applied.

In the discriminator, the image is processed through ordinary strided convolutions with LeakyReLU activation. At the output, we have one neuron with a sigmoid function, which derives the probability that the image is real.

The minimax loss function GAN describes the classic competition between generator and discriminator:

min_G max_D E_x[log D(x)] + E_z[log(1 - D(G(z)))].

Formula 5. GAN MinMax loss function [20]

To stabilize the learning process, the authors use Batch Normalization in most layers, excluding the input discriminator and the output of the generator. Fully connected layers are also removed, which reduces the number of parameters and improves generalization. Optimization takes place using Adam with a low learning coefficient (0.0002) and a reduced momentum parameter ($\beta_1 = 0.5$), which helps to avoid fluctuations during learning.

The main experimental part is devoted to testing the ability of DCGAN to study qualitative features of images under uncontrolled conditions. On the large LSUN dataset with over 3 million room images, DCGAN demonstrates the ability to generate photorealistic bedrooms even after one pass (epoch) through the data.

Fig. 2.10. Generated rooms after one pass on LSUN [20]

Fig. 2.11. Generated rooms after five eras [20]

Another interesting part of the study is the use of a discriminator as a feature extractor. The model trained on ImageNet showed good generalizing ability, reaching 82.8% accuracy on the CIFAR-10 without any additional training.

Table 2.6

Classification of CIFAR-10 using features from DCGAN (DCGAN was not trained in CIFAR-10, only used as a feature extractor [20]

Model	**Точність**	**Accuracy (400 samples/class)**	**Number of characteristics (units)**
1-layer K-means	80.6%	63.7% (±0.7%)	4800
3-layer K-means (Learned RF)	82.0%	70.7% (±0.7%)	3200
View Invariant K-means	81.9%	72.6% (±0.7%)	6400
Exemplar CNN	84.3%	77.4% (±0.2%)	1024
DCGAN (наше) + L2-SVM	82.8%	73.8% (±0.4%)	512

No less interesting are the properties of the generator. The authors demonstrate the "arithmetic of vectors" in latent space.

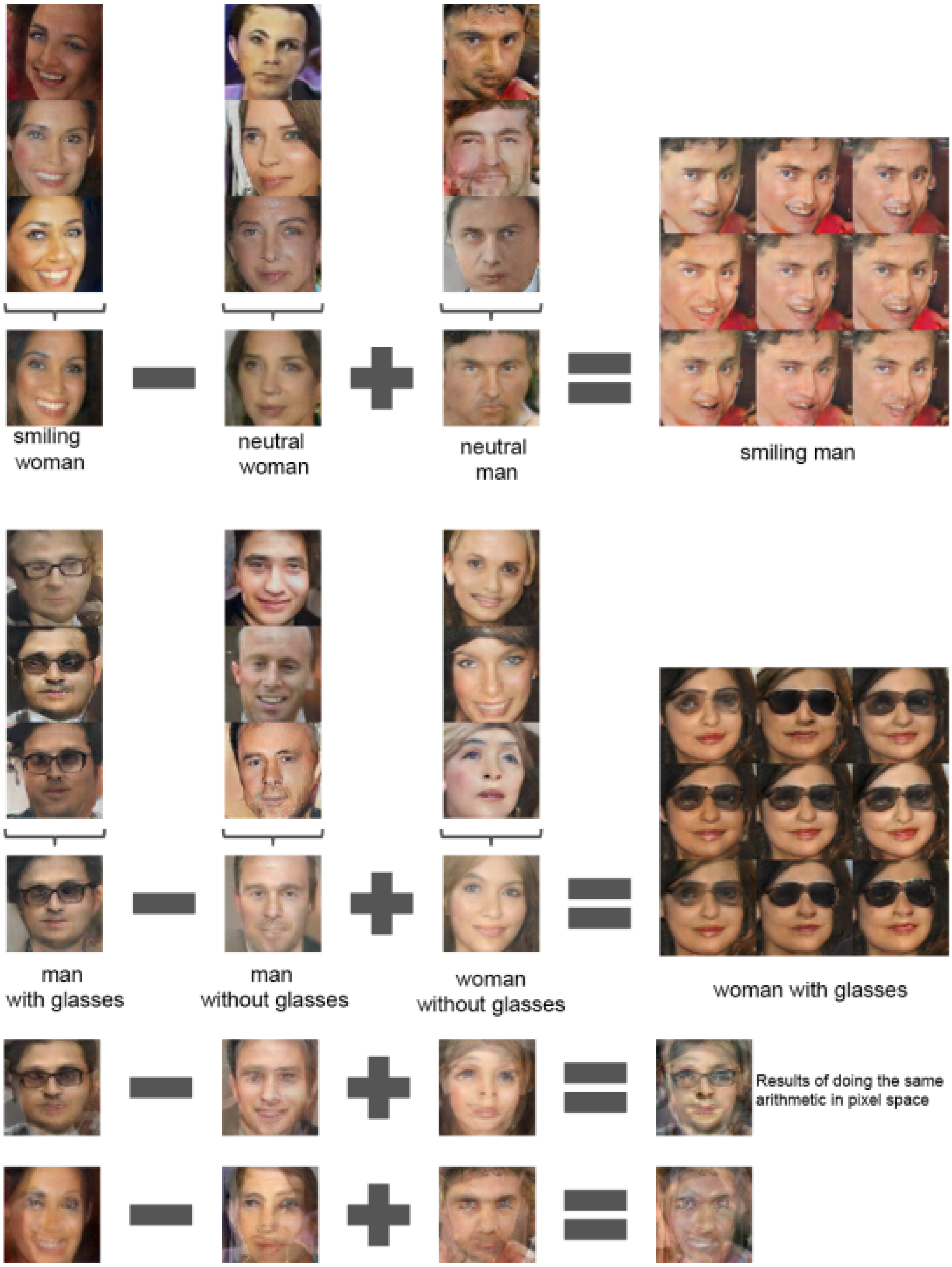

Fig. 2.12. Manipulation of facial posture using Z-vectors [20]

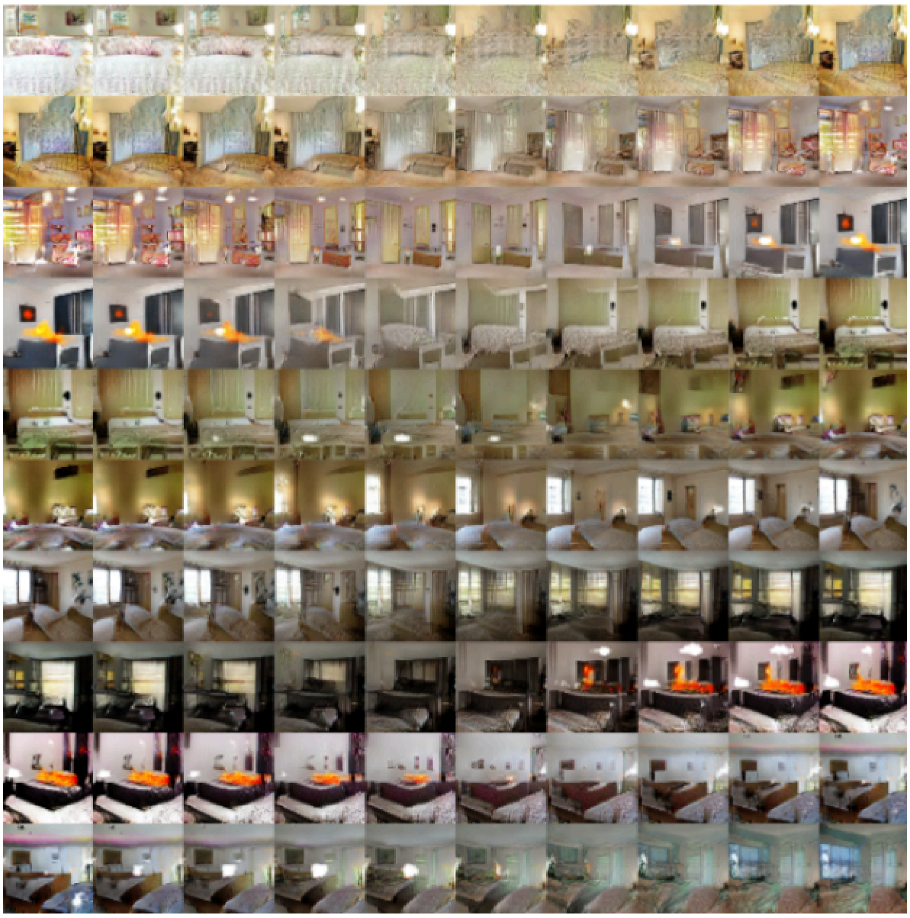

Fig. 2.13. Example of vector arithmetic in latent space [20]

In addition, the authors are experimenting with turning off certain filters in the generator in order to "forget" how to draw objects - for example, windows.

As a result, the article by Radford and colleagues was a key milestone in the development of generative models. It shows that DCGAN is not only a tool for creating images, but also a powerful architecture for teaching representations without markup.

Review of the scientific article: "Improved Techniques for Training GANs" [25] Written by Tim Salimans, Ian Goodfellow, Wojciech Zaremba, Alec Radford, Vicky Cheung, Xi Chen.

The article provides a number of new architectural features and training procedures applied to generative adversarial networks (GAN). The focus is on two applications of GAN: semi-supervised learning and generating images that people consider visually realistic. Unlike most work in the field of generative models, the goal of research is not to train a model that assigns a high probability to test data, and it is not necessary that the model be well trained without applying any labels.

The authors achieve the most up-to-date results in a semi-controlled classification on MNIST, CIFAR-10 and SVHN. The generated images are of high quality, as confirmed by the visual Turing test: the model generates MNIST samples that people cannot distinguish from real data, and CIFAR-10 samples giving a human error rate of 21.3%. ImageNet samples with unprecedented resolution are also presented and it is shown that the methods allow the model to study recognizable features of ImageNet classes.

GAN is a class of methods for teaching generative models based on game theory. The goal of GAN is to train a generator network G (z; θ (G)) that produces samples from a data distribution p_data (x) by converting noise vectors z as x = G (z; θ (G)). The learning signal for G is provided by the discriminator network D (x), which learns to distinguish samples from the distribution of the generator p_model (x) from real data. The generator network G, in turn, learns to deceive the discriminator, forcing it to take its outputs for real ones.

Although GANs can produce excellent samples, learning them requires finding a Nash equilibrium in a non-convex game with continuous multidimensional parameters. GANs are usually trained using gradient descent techniques designed to find the low value of the objective function rather than finding the Nash equilibrium in the game. When trying to find a Nash equilibrium, these algorithms may not converge.

In this work, the authors present several techniques aimed at encouraging the convergence of the GAN game, based on a heuristic understanding of the problem of incontinence.

$$\left\| E_{x \sim p_{data}} f(x) - E_{z \sim p_z(z)} f(G(z)) \right\|_2^2$$

Formula 6. Loss function formula for the *Feature Matching* method [25] where , $x \sim p_{data}$ - sample from x distribution of true data , $z \sim p_z(z)$ - sampling the noise z of the latent space (e.g. normal distribution), G(z) - image generated by the noise generator z, $f(\cdot)$ - feature vector (feat representation) on one of the intermediate layers of the disruptor (for example, before the last layer), E - expectation (mean), $||\cdot||_2^2$ - L2-norma (Euclidean distance squared).

This formula defines a new objective function for the generator, where it learns to generate data corresponding to real data statistics by matching the expected feature value on the intermediate layer of the discriminator.

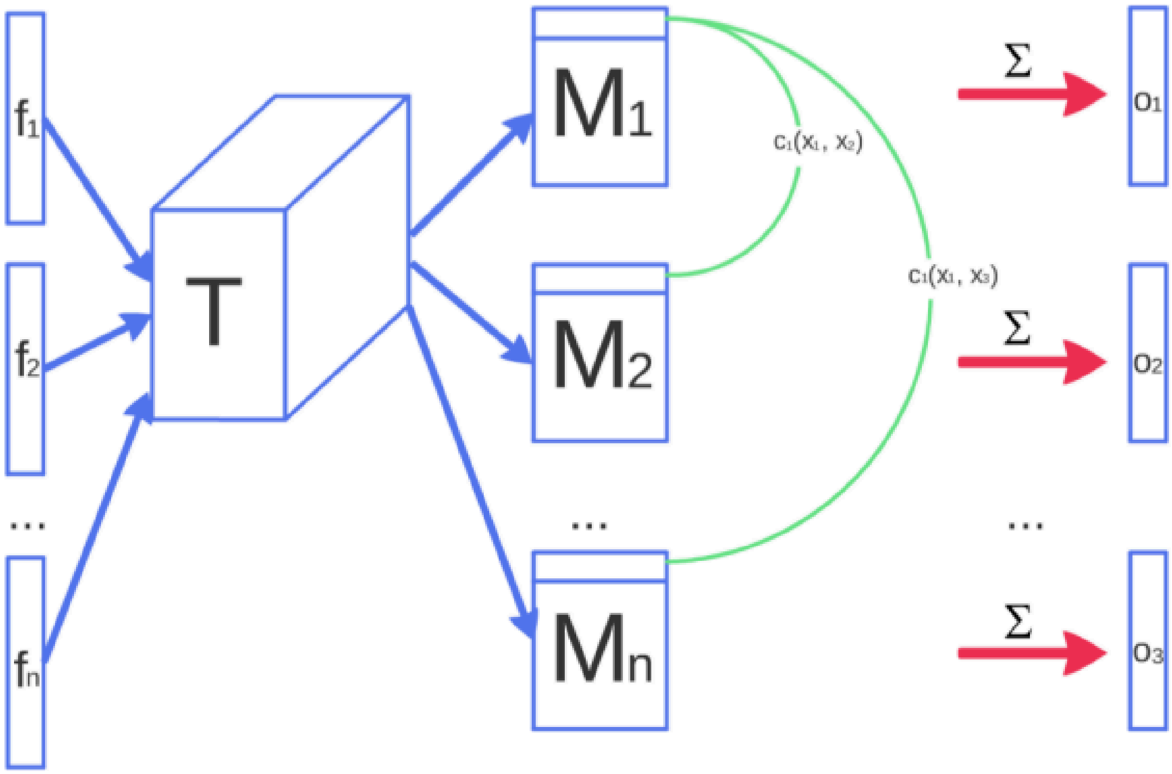

Fig. 2.14. Minibatch Discrimination architecture [25]

Minibatch Discrimination is a technique that allows the discriminator to "see" the differences between entire mini-packets of generated and real examples, rather than handling them in isolation

In the article, the authors explain that Batch Normalization (BN) is very useful for training deep neural networks, and it is also effective for DCGAN. However, BN has a drawback: the output of the neural network for a particular input example becomes highly dependent on other input examples in the same mini-packet. This can be a problem, especially for a generator in a GAN where it is desirable that the generated examples be more independent of each other.

To solve this problem, the authors propose Virtual Batch Normalization (VBN). That is how it works:

- Reference mini-package: First, one "reference" mini-package of examples is selected and fixed at the beginning of the training.
- Normalization: When we normalize a particular example, we do so based on the statistics collected on that reference packet as well as on that example itself. In other words, we use the mean and variance of the reference packet, combining them with the value of the example itself, which we normalize.
- Reference packet normalization: The reference packet itself is normalized using only its own statistics (i.e., the average and variance of that packet).

VBN allows the generator to learn, reducing the dependence of the output for a particular example on other examples in the current mini-package. This can help stabilize learning and prevent unwanted correlations between generated samples.

The authors note that VBN is computationally expensive because it requires forward propagation through the network for two mini-data packets. Because of this, they only use the VBN in the generator network.

Table 2.7

Comparison of CIFAR-10 and SVHN errors on different models [25]

Model	Error on CIFAR-10	Error on SVHN
1	2	3
Baseline GAN	28.17	24.11

Table 2.7 (Continued)

1	2	3
Feature Matching GAN	19.64	18.63
Minibatch Discrim. GAN	22.48	20.43
Virtual Batch Norm GAN	21.15	19.92

The table shows that the proposed techniques improve the results of semi-controlled classification on CIFAR-10 and SVHN.

In conclusion, the papers show several new methods that help stabilize GAN learning and increase their effectiveness in image generation and semi-supervised learning. They consist of Feature Matching, Minibatch Discrimination, and Virtual Batch Normalization. The authors hope that these methods will be the beginning of future research, providing formal guarantees of GAN convergence.

This article may be useful for a diploma project as it offers specific solutions to stabilise GAN learning, which is an important issue in the field. The proposed methods can be used or adapted to improve GAN learning in your own project, especially if you are working with image generation or semi-supervised learning.

2.3. Problem statement for structurally parametric synthesis of DCGAN

In modern medical problems, in particular in the diagnosis of skin cancer, one of the main problems is the limited number of qualitatively annotated images, especially for rare or aggressive types of neoplasms (for example, melanoma). Insufficient training data leads to low generalizing ability of models and increased risk of retraining.

Another significant problem noted by the authors [20] is the instability of generative adversarial networks (GANs) during training. In particular, the phenomena of mode collapse, the disappearance of gradients and the inability to generate variable images are typical. To partially eliminate these problems apply:

- Batch Normalization;
- ReLu / LeakyReLu activation function .

As part of my research, a hypothesis was put forward about the possibility of building a unified architecture that combines image generation and classification of the type of lesion (benign/malignant). The primary task was to create a stable DCGAN architecture capable of:

- generating synthetic images of skin lesions;
- automatic classification of the type of lesion using a discriminator as a neural classifier.

However, in the course of practical experiments, it was found that generation does not provide the necessary image quality, while the adapted discriminator showed high efficiency in the binary classification problem.

A generative-adversarial network consists of two components - generator G and discriminator D, which are trained in the form of a zero-sum game (see Formula 5).

The loss functions for the generator and discriminator look like this:

Discriminator losses:

$$L_D = -\frac{1}{m}\sum_{i=1}^{m}[logD(x_i) + log(1 - D(G(z_i)))];$$

Formula 7. Discriminator loss formula

Loss of generator:

$$L_G = -\frac{1}{m}\sum_{i=1}^{m} logD(G(z_i));$$

Formula 8. Generator loss formula

Since the discriminator in our system additionally classifies the type of skin lesion, the Categorical Cross-Entropy function is used for this (see Formula 10).

Formulation of the problem of structural-parametric synthesis:

- Structural synthesis: modification of the number of convolutional layers, the number of filters, the size of nuclei, the size of latent space.
- Parametric synthesis: tuning of Adam optimizer parameters (β_1, β_2), learning rate, batch size, number of epochs.
- Classification function: Use the Categorical Cross-Entropy function to train the discriminator as a classifier.

Thus, the final goal was to create an intelligent diagnostic system that, based on the modified DCGAN architecture, can effectively classify skin lesions, which is confirmed by empirical metrics of accuracy, recall, F1 and AUC.

CHAPTER 3.
INTELLIGENT MEDICAL DIAGNOSTIC SYSTEM FOR SKIN CANCER CLASSIFICATION

3.1. General characteristics of the created systems

As part of the thesis project, an intelligent medical diagnostic system for skin cancer classification based on the architecture of deep convolutional neural networks was implemented. The initial goal was to explore the possibilities of generative-competitive networks (in particular, DCGAN) as a tool for synthesizing images of skin lesions. However, in the course of development, the focus was shifted to the adaptation of the DCGAN discriminator as a classifier, as well as the introduction of an alternative architecture - ResNet18 - to improve classification accuracy.

The development of the system consisted of several stages, including:

- preliminary testing of the DCGAN architecture on the CIFAR-10 base set;
- image preprocessing (normalization, augmentation);
- scaling the model to work with medical images from the ISIC 2019 set (image size 64×64);
- a series of experiments with the architecture of the generator and discriminator aimed at overcoming the problem of repeated images and mode collapse;
- analysis of classification efficiency based on the discriminator. quality assessment by metrics: precision, recall, F1, accuracy, AUC;
- using GPU to speed up computing.

The main goal of the system is to implement a reliable intelligent medical diagnostic system for classifying skin lesions into two classes: benign and malignant, using deep learning methods. In this context, the DCGAN generator played an experimental role: it was implemented and tested, but due to the insufficient quality of the generated images, it was not integrated into the classification pipeline. Thus, the system is not a full-fledged "generative-classification" pipeline, but rather a classification system with a research generation module.

The overall structure of the system is as follows:

- images of skin lesions preliminarily divided into two classes: benign and malignant; preliminary processing - normalization and augmentation;
- Classification model: architecture of a DCGAN discriminator or ResNet 18 that receives an image as an input and outputs a probability of belonging to one of two classes;
- Training: performed on GPU, taking into account the imbalance of classes (due to loss weights), optimized with Adam;
- Output: image class ("benign" or "malignant") along with quality metrics (accuracy, precision, recall, F1, AUC).

Program environment:

- Programming language: Python 3.10
- Libraries: PyTorch, NumPy, Matplotlib, Pandas
- Calculations were performed in PyCharm using CPU and GPU (NVIDIA GeForce RTX 3060), Google Colab using GPU (NVIDIA Tesla 14)

Architectural features:

To ensure stable learning, we followed the basic recommendations from Radford et al [20]:

- the generator (at the stage of experimental study) used ReLU activations on all layers except the last one (Tanh);
- LeakyReLU activations were used in the discriminator that was adapted for classification;
- Batch Normalization - on all intermediate layers to stabilize gradients;
- as a loss function for classification, "CrossEntropyLoss' was used with class weights to combat imbalance;
- optimization was performed using the Adam algorithm with a learning rate of 0.0002 and parametersβ_1 = 0.5, β_2 = 0.999.

Table 3.1

Comparative structure of the main components of the generator and classifiers (DCGAN, ResNet18)

Component	**Layer type**	**Activations**	**Normalization**
Generator(experiment)	ConvTranspose2D (stride=2)	ReLU, Tanh	BatchNorm
DCGAN-classifier	Conv2D (stride=2)	LeakyReLU, Softmax	BatchNorm (all but the first layer)

All convolutional and deconvolutional layers in the DCGAN discriminator and generator architectures operated with stride = 2. This made it possible to effectively change the dimensionality of the images while preserving the spatial structure by applying padding, which adds a frame of zeros around the input data to avoid losing information at the edges.

This system has several key advantages:

— Flexible architecture: two classification approaches are implemented - based on the adapted DCGAN discriminator and the convolutional network ResNet18. Both can be modified for multi-class or multi-label classification;

— Versatility: Image processing is performed in a standardized format (size, channels, normalization), which allows the system to be adapted to other medical applications, such as histopathological analysis, dermatosis diagnostics, X-rays, etc;

- Computational efficiency: Using ResNet18 with pre-trained weights (ImageNet) reduces the need for large amounts of data and speeds up the training process;
- Possibility of further data generation: even though the DCGAN generator is not used in the final classification system, its presence opens the way to synthetic augmentation of datasets (data augmentation via GANs).

At the same time, the system has certain limitations related to the imbalance of classes, the limited quality of synthetic images, and the variability of results when changing architectures. These aspects will be discussed in the following sub-sections. Nevertheless, the model lays a solid foundation for further research and integration into practical medical diagnostic systems.

3.2. Architecture and operation of the generator (DCGAN)

When implementing the generator, we took into account the recommendations of Radford et al. (2016)[20] regarding architectural stability. In particular, all layers used padding 1 (padding=1), which allowed us to maintain a consistent geometry during scaling. In some experiments, an alternative kernel size of 8x8 for the last layer was tested, but this led to dimensional errors. The final version of the generator uses the classical configuration - 4×4 kernels with stride = 2.

Activation functions:

- ReLU - on all hidden layers, which ensured stable learning;
- Tanh - on the original layer, allowed to normalize the pixel intensity to the range [-1, 1].

Training:

- The loss function is Binary Cross-Entropy;
- The optimizer is Adam (learning rate = 0.0002, B1 = 0.5);
- The initialization of the weights is a normal distribution with a standard deviation of 0.02.

During the training, the generated images were saved at control epochs (5, 10, 20, 50), which allowed us to visually assess progress. The first structured fragments appeared after 15-20 epochs, and stable generation after 40-50 epochs.

Conclusion: The generator implemented in this work demonstrated the ability to generate images of 128x128 pixels. However, due to insufficient image quality in the early stages, it was not used in the final classification system. In further research, it can be adapted to generate synthetic examples of rare classes (data augmentation).

Table 3.2

General structure of the generator

Layer №	Layer type	Kernel size	Step	Output channels	Activation	Note
1	Dense + reshape	—	—	1024	ReLU	From the vector z → 4×4×1024
2	ConvTranspose2D	4×4	2	512	ReLU	BatchNorm
3	ConvTranspose2D	4×4	2	256	ReLU	BatchNorm
4	ConvTranspose2D	4×4	2	128	ReLU	BatchNorm
5	ConvTranspose2D	4×4	2	3	Tanh	Output: RGB image 128×128

Clarification to *Table 3.9* In the final version of the system, 64 x 64 images were used, but at the time of the generator implementation, 128 x 128 photos were still used. After Dense-reshape, the number of output channels varied depending on the ndf configuration. In the final layer, the output channels contained 3 x 128 x 128 (or 3 x 64 x 64) images

3.3. Construction of the discriminator and its dual role

The discriminator was initially implemented in the classical DCGAN form: as a convolutional neural network that learns to distinguish between real images from the dataset and those generated by the generator. The architecture includes several consecutive convolutional units (Conv2D + BatchNorm + LeakyReLU) that gradually reduce the spatial resolution of the input image.

The output of the discriminator is the probability of image authenticity, but in our case, it was adapted for an additional task - binary classification of the type of skin lesion. For this purpose, the last layers of the model were transformed into a fully connected structure with Softmax or LogSoftmax, which returns two probabilities for the classes "benign" and "malignant".

Thus, the discriminator in the implemented system plays a dual role:

- As part of a generative network, as a critic who helps to train the generator;
- As part of the classification subsystem, it is the main classifier trained on real data.

This approach allows not only to reuse the same architecture but also to save resources during training by reducing the number of parameters and computation time.

In further experiments, we also used the pre-trained ResNet model 18 to compare the classification quality. Nevertheless, even the DCGAN discriminator demonstrated satisfactory results, especially when the classes were properly balanced and the hyperparameters were tuned.

Table 3.3

General structure of the discriminator

Layer №	**Layer type**	**Kernel size**	**Step**	**Output channels**	**Activation**	**Note**
1	Conv2D	4×4	2	64	LeakyReLU	No formula normalization
2	Conv2D	4×4	2	128	LeakyReLU	BatchNorm
3	Conv2D	4×4	2	256	LeakyReLU	BatchNorm
4	Conv2D	4×4	2	512	LeakyReLU	BatchNorm
5	Conv2D (output)	4×4	1	1 або 2	Sigmoid/Softmax	1 — for GAN, 2 — for classification

In the discrimination mode (generator vs. discriminator), the output channel is set to 1 and Sigmoid is used to estimate the probability that the image is genuine.

In the classification mode, the output channel is changed to 2, and Softmax is applied to estimate which of the two classes (benign/malignant) the image belongs to.

Advantages of the approach:

- Resource saving: one unit is used for two tasks without the need to create a separate classification network.
- Preliminary training on a generative task gives the discriminator a deeper understanding of the texture, color, and morphology of skin lesions.
- Improved generation: a discriminator that has a deeper understanding of classes provides the generator with more accurate feedback.

Learning and loss:

- Binary Cross Entropy Loss (BCE) is used for the classical discrimination problem.
- For classification by 2+ (in our case, two - benign/malignant) classes, Categorical Cross Entropy is used if the discriminator is used as a classifier.

$$L_{BCE} = -\ [y log(D(x))\ +\ (1\ -\ y) log(1\ -\ D(x))],$$

Formula 9. Binary cross entropy

where : L_{BCE} - Binary Cross Entropy; x - input image (real or generated); $y \in \{0,1\}$ is the real label : 1 for a real image , 0 for a generated image; $D(x) \in (0,1)$ - is the output of the discriminator: an estimate of the probability that the image is real.

This function is minimized when the discriminator correctly determines the class of each image, i.e., it outputs $D(x) \approx 1$ for a real image and $D(x) \approx 0$ for a fake image.

$$L_{CE} = -\sum_{i=1}^{C} y_i log(\widehat{y_i}),$$

Formula 10. Categorical Cross Entropy

where : L_{CE} - Categorical Cross Entropy; C=2, i.e. classes: benign, malignant; $y_i \in \{0,1\}$ - the true one-got label for class i (for example, if the image belongs to the malignant class, then y = [0,1]); $\hat{y}_i \in (0,1)$ - is the probability predicted by the network for class i , such that $\sum_{i=1}^{C} \hat{y}_i = 1$.

Conclusion: The adaptation of the DCGAN discriminator for dual use - first as a critic in the generative network and then as a classifier - allowed us to maximize the use of limited computing resources and training data. Although the generative part was not included in the final model, it was the preliminary training of the discriminator on the task of recognizing fake images that contributed to a better understanding of the structures of skin lesions. This approach shows promise for creating compact, versatile systems that can combine generation and diagnosis, which is important in medical applications with limited data.

3.4. Comparison with the reviewed works

The system implemented in this thesis combines generative and classification approaches based on DCGAN, which distinguishes it from most of the solutions considered in the literature.Integration of generation and classification (unlike Behara et al. [17])

In the paper "Skin Lesion Synthesis and Classification Using an Improved DCGAN Classifier" [17], generation and classification are implemented as separate stages: a DCGAN is used for generation, and a separate CNN is used for classification. Instead, in my implementation, the DCGAN discriminator is modified in such a way that it performs a dual function: as a realism estimator during generation and as a classifier for real images. This reduces the number of parameters and simplifies the overall architecture.

Optimization for 128×128 medical images (unlike Radford et al. [20])

In the classic paper "Unsupervised Representation Learning with DCGAN" [20], the dimensionality of 64x64 is used, which is typical for everyday tasks (LSUN, Imagenet). In my system, the DCGAN was adapted to images of 128×128 from the

ISIC 2019 set, which meets the medical requirements for diagnosing dermatological lesions.

Focus on practical application (unlike Jenkins & Roy [18])

In the publication "Exploring DCGAN in Biometric Systems" [18], DCGAN is only analyzed as a potential tool for biometrics, without a specific implementation on medical data. In my work, DCGAN was practically implemented and adapted to a medical task with a clearly defined application scenario - classification of skin lesions.

Stability control and manual optimization (based on Salimans et al. [25])

In accordance with the advice from the paper "Improved Techniques for Training GANs" [25], we implemented the basic recommendations: we used BatchNorm, LeakyReLU, and the corresponding hyperparameters of the Adam optimizer. In addition, visual control over the quality of generation, loss monitoring, and mode collapse detection were performed.

Limitations of the implemented system :

- Lack of advanced techniques from [25]. The system does not implement such approaches as mini-batch discrimination, feature matching or historical averaging, which limits its stability when generating complex textures.
- Limitations to binary classification. The current implementation works with only two classes (benign/malignant), which, although it simplifies the structure, limits the flexibility for advanced tasks (for example, multi-class diagnostics).
- Basic data processing . Pre-processing included only resize, normalization, and class sorting. Unlike [17), no specialized filtering or contrast enhancement methods were used.

The implemented system demonstrates a competitive architecture that combines generation and classification in one framework. Despite some simplifications, it is based on the proven architectural principles of DCGAN and has the potential for further improvement, in particular by implementing modern stabilization techniques.

3.5. Stages of data preparation and model training

In the process of creating an intelligent system, special attention was paid to the stage of data preparation. As you know, even the most efficient architecture loses its potential with a poor-quality or unstructured dataset. Therefore, the first task was to build a reliable pipeline of preprocessing.

Preliminary stage: checking the architecture for CIFAR-10

Initially, a set of CIFAR-10 was used to test the DCGAN architecture. This made it possible to check the correctness of the network construction, the stability of the loss functions, as well as to identify typical problems, such as the disappearance of gradients or mode collapse. Although the results of the generation were weakly informative, this experiment made it possible to verify the operability of the system before switching to real medical data.

Main stage: preparation of ISIC 2019

The main source of images was the ISIC 2019 kit, which includes a large volume of dermatological images of various types of skin lesions. The following was performed:

- unification of sizes up to 128 × 128 pixels;
- normalization of pixel values to the range [−1, 1], which is consistent using the Tanh function;
- classifying images into two classes:
  - Benign: NV, BKL;
  - Malignant: MEL, BCC, AKIEC, etc.

Classes were automatically distributed based on a CSV file with labels and corresponding sorting by subdirectories.

The analysis revealed a significant imbalance in favor of the benign class, which is typical for medical datasets. To compensate for it, the following were used:

— class weights in the class weights function

— planned generation of synthetic malignant images from the generator side (experimental part).

DCGAN has trained for 50 eras with the following parameters:

— optimizer : Adam;

— learning rate = 0.0002;

— $\beta_1 = 0.5$;

— функція втрат: Binary Cross Entropy;

— batch size = 64.

Augmentation (horizontal flips, turns) was not deliberately used so as not to distort the morphological characteristics of skin lesions. However, in future versions of the system, this can be integrated.

After every few eras, examples of generated images were stored for visual analysis. The values of the loss functions of the generator and discriminator were also monitored, which made it possible to timely identify an imbalance in training (for example, the superiority of one of the components or the mode collapse feature).

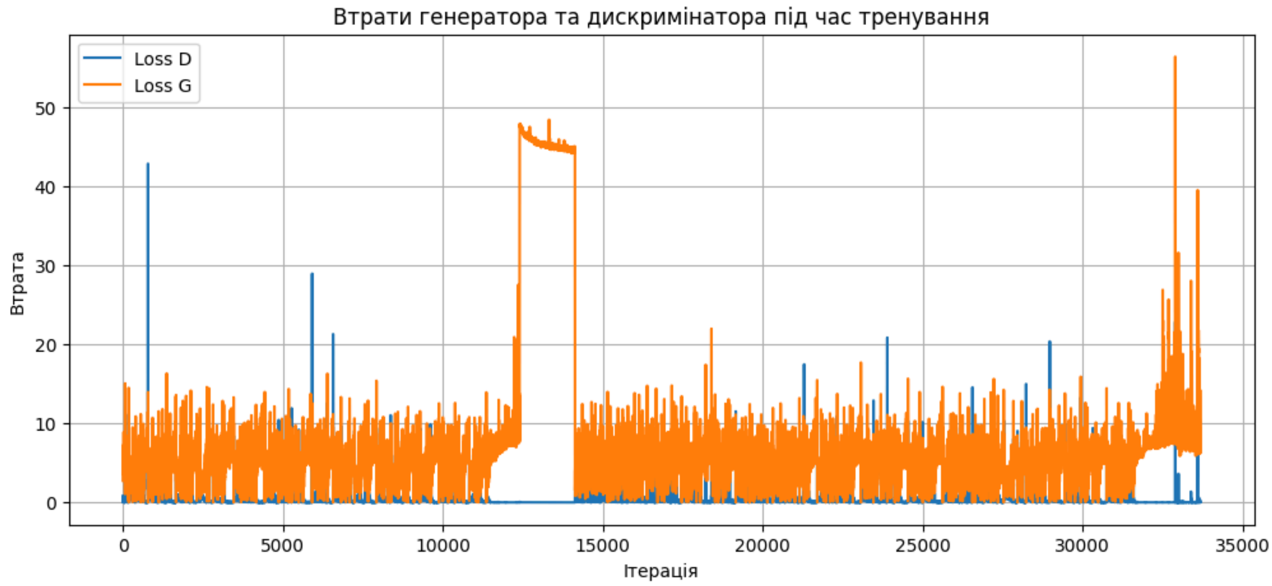

Fig. 3.1. Loss of generator and discriminator during CIFAR-10 training

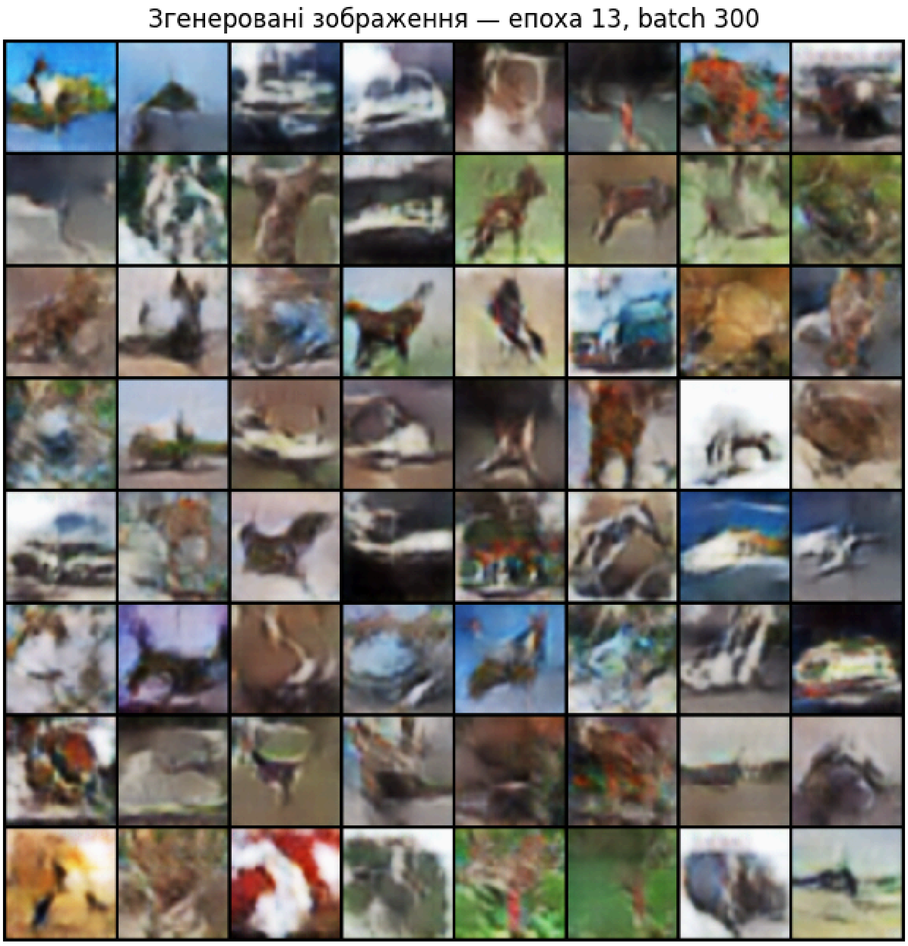

Fig. 3.2 Generated images on the CIFAR-10

3.6 Conclusions to Section

As a result of this phase of the project, an intelligent diagnostic system capable of performing binary classification of skin lesions with a sufficient level of accuracy was built. Two architectures were tested: the modified DCGAN discriminator and the ResNet18. Both models showed working results, but it was ResNet18 who achieved the best generalizing ability.

Although the DCGAN generator was not integrated into the final system, its implementation made it possible to better understand the dynamics of GAN architectures and made it possible to expand the dataset in the future. Importantly, the DCGAN discriminator can be adapted for classification problems without complete re-projection.

Thus, the created system has a clear practical orientation, provides sufficient flexibility for further modifications and can be the basis for more complex multi-class or multimodal solutions in medical diagnostics.

CHAPTER 4.
ANALYSIS OF SYSTEM OPERATION RESULTS

4.1. Analysis of classification results

The main purpose of the developed system was to ensure the effective classification of images of skin lesions into two categories: benign (benign) and malignant (malignant). This subsection presents the results of the work of two main models - the adapted DCGAN discriminator and the ResNet18 architecture, which served as a reference.

The training was conducted on a subset of the ISIC 2019 dataset, bringing all images to 128 × 128 pixels. Various combinations of parameters were tested, in particular class weights in the loss function, the number of epochs, the use of GPU acceleration.

Table 4.1

Basic classification metrics

Architecture	Accuracy	Precision	Recall	F1	AUC
DCGAN-discriminator	~0.60	~0.65	~0.50	~0.56	~0.59
ResNet18	~0.74	~0.73	~0.72	~0.72	~0.71

During the analysis, graphs of the dependence of loss functions on the number of epochs were also built.

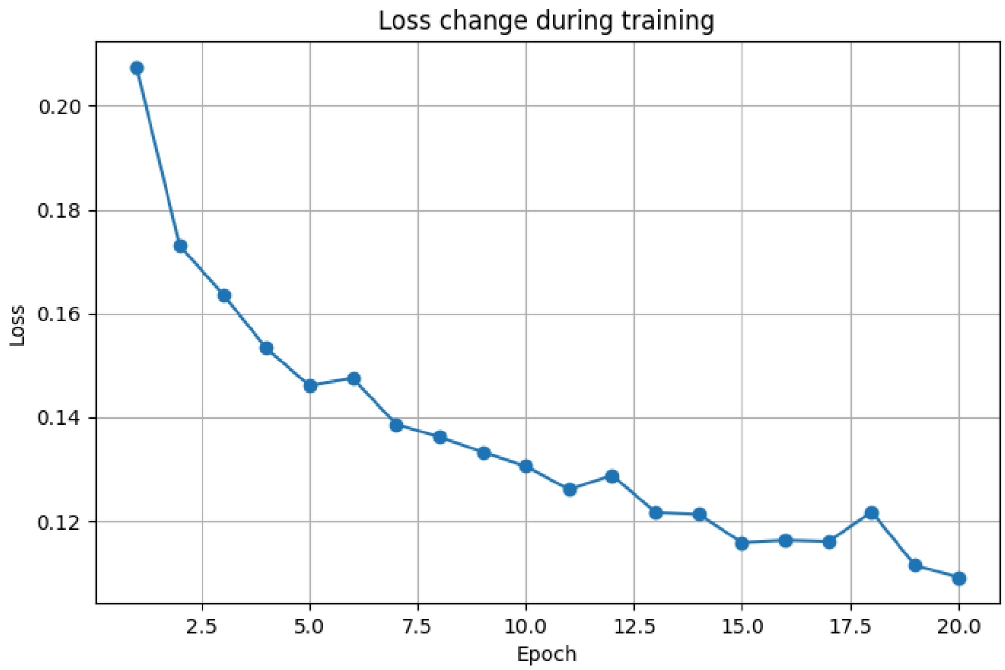

Fig. 4.1 DCGAN discriminator loss graph

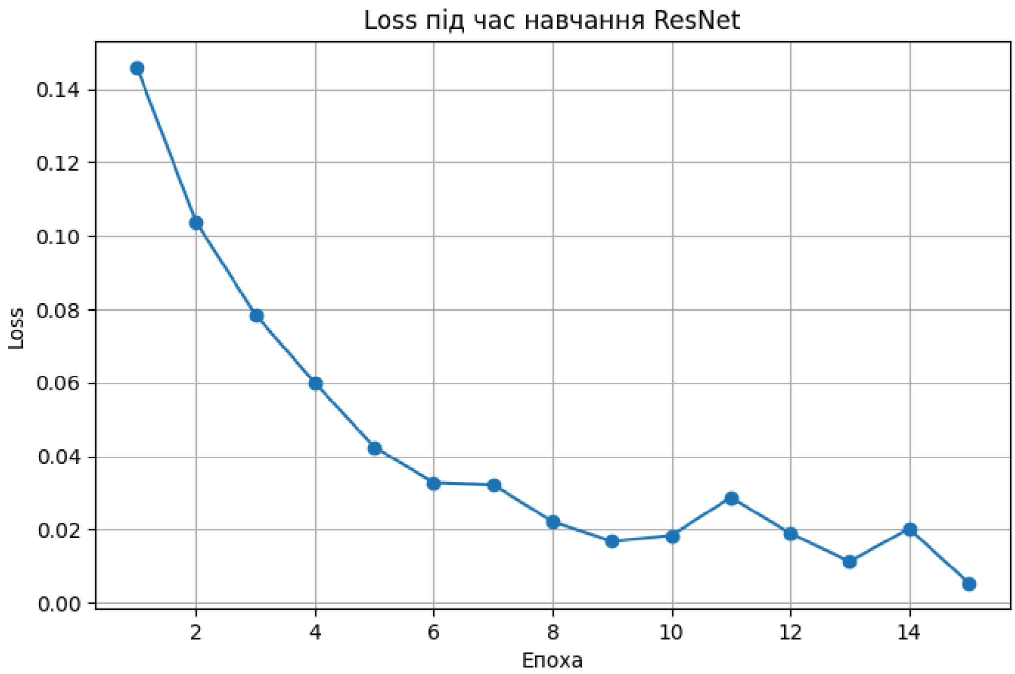

Fig. 4.2 ResNet loss graph

Confusion Matrix (ResNet18):

The ResNet18 model showed good sensitivity to malignant lesions, although it had individual errors of the second kind (false negative), which is critical in medical diagnosis.

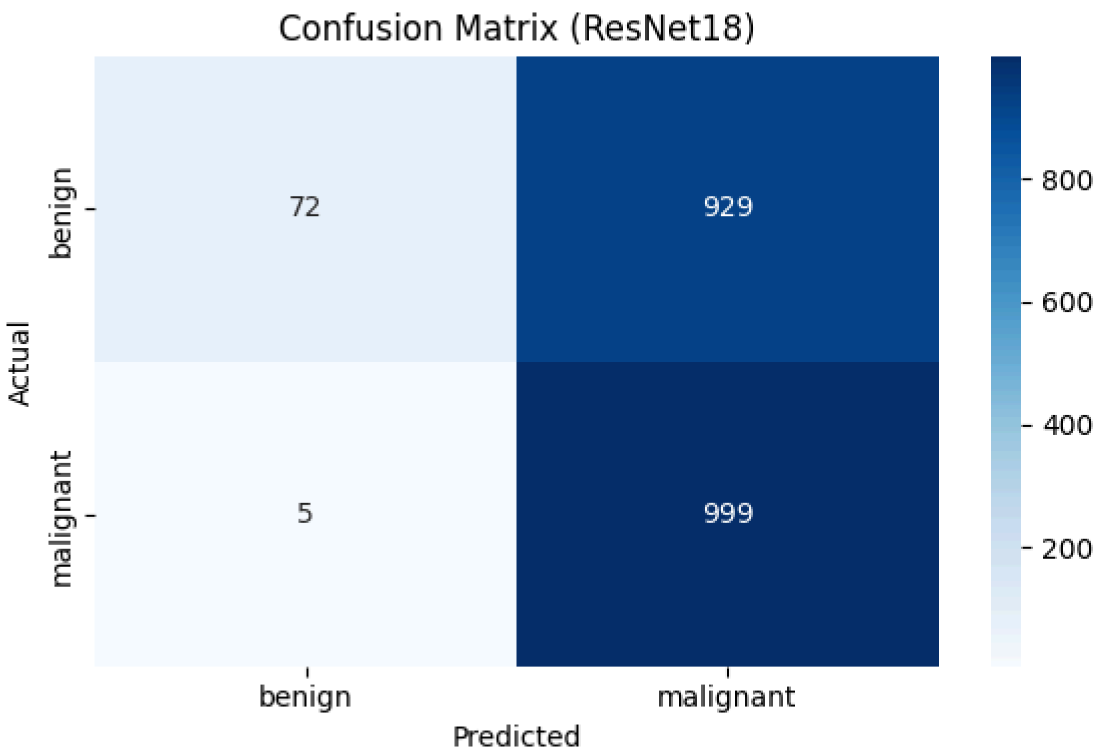

Fig. 4.3 ResNet 18 confusion matrix

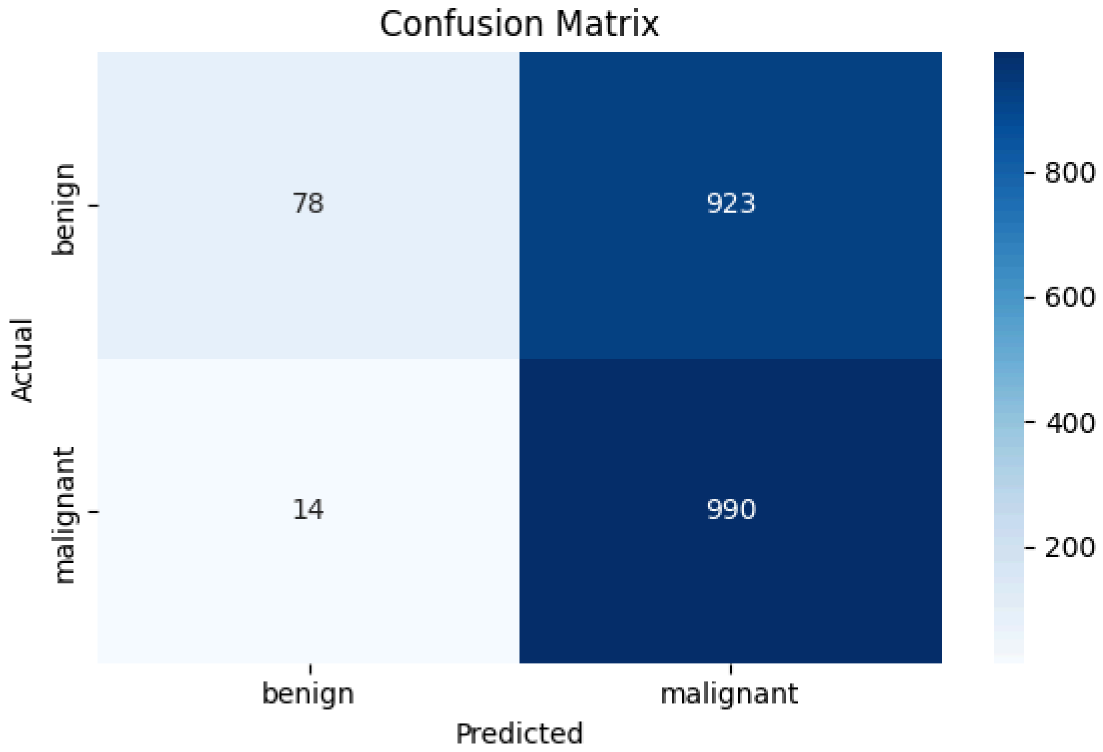

Fig. 4.4 DCGAN discriminator confusion matrix

In the case of the DCGAN discriminator, the predominance of one of the categories is noticeable, which may be due to class imbalance or architectural limitations.

The AUC for ResNet18 was ~ 0.71, indicating the high ability of the model to separate the two classes. For DCGAN, this figure was lower (~ 0.59), but still shows some classification ability even without direct adaptation to the classification problem. The ROC charts clearly show how ResNet18 provides a better trade-off between sensitivity and specificity compared to DCGAN.

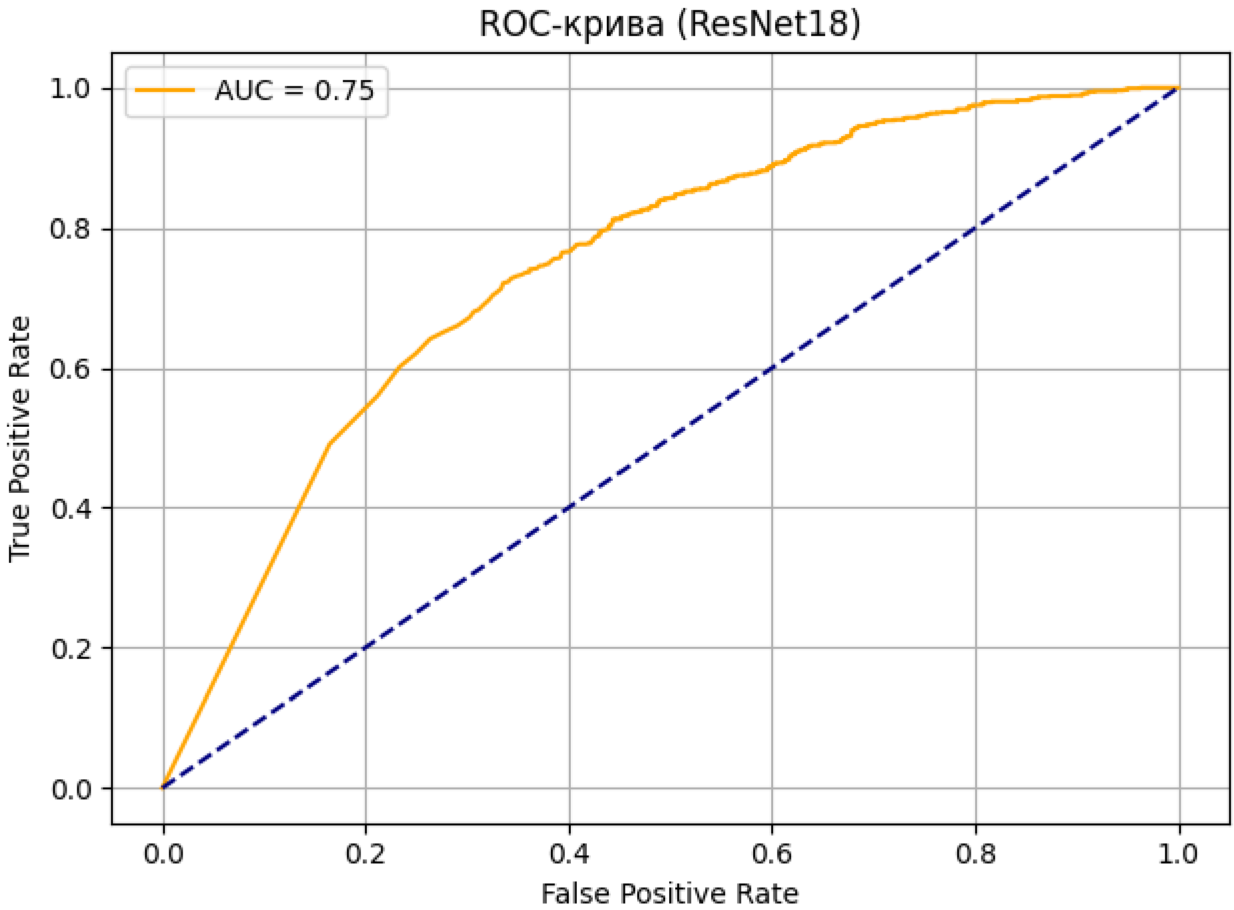

Fig. 4.5 ResNet18 ROC-curve

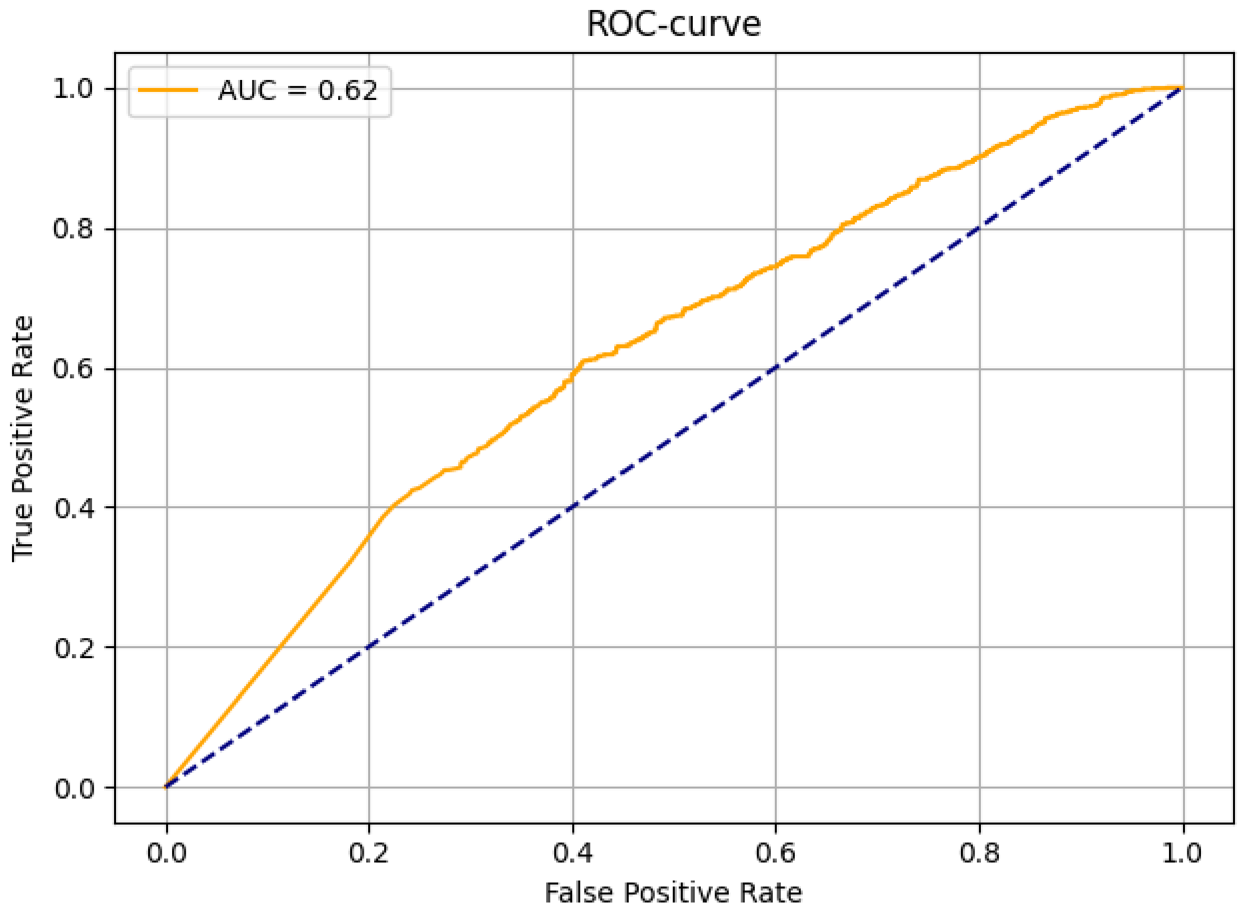

Fig. 4.6. DCGAN discriminator ROC-curve

Conclusions: The comparison of the two architectures confirms the superiority of ResNet18 as a classification model in a medical context. Nevertheless, DCGAN remains important as a demonstration of the possibility of reusing generative components, as well as a promising base for further research and expansion (for example, multi-class classification, few-shot learning, etc.). At the same time, loss graphs and ROC curves allow us to conclude that the discriminator can be used in problems where computational resources are limited or rapid prototyping with minimal architectural changes is required

4.2. Dynamics of loss functions

This subsection analyzes the dynamics of changes in loss functions during the training of both models - DCGAN discriminator and ResNet18. This analysis allows us to draw conclusions about the stability, the rate of convergence and the overall learning process of the models.

DCGAN-discriminator (see Fig. 25):

In the first 5-10 epochs, there was a rapid decrease in the loss function, which may indicate a rapid adaptation of the model to the basic patterns in the data. However, after the 10th era, signs of retraining or instability began to appear: the loss schedule showed fluctuations, the loss of the generator and discriminator began to diverge, which is a typical symptom of mode collapse.

In some experiments, the loss discriminator fell to very small values (~ 0.1), and the generator began to produce pattern or noise images. This confirms the need for a more subtle selection of hyperparameters or the use of stabilizing methods (for example, gradient penalty).

ResNet18 (see Fig.24):

The loss function of classification declined gradually and steadily throughout the 20 eras. The graph had a classical form - an exponential fall in the first epochs, followed by alignment. The absence of sharp jumps indicates well-chosen learning parameters and high consistency of architecture with the medical dataset.

ResNet18 was expected to show higher stability and better convergence. The DCGAN discriminator, despite the unstable dynamics of losses, still reached an acceptable level of classification, which is especially impressive given that the model was originally developed as part of a generative network, and not a separate classifier.

The next section (4.3) will consider in more detail how these losses affected the classification ability of the model and what conclusions can be drawn from the behavior of the metrics on the test sample.

4.3. Evaluation of the generative system

The generative component of the system - that is, the DCGAN generator unit - was tested in order to determine its ability to create visually plausible images of skin lesions that can be used to replenish unbalanced medical datasets.

Several generator runs were conducted based on a random noise vector z∈R100, with the following visualization of the results after: 5 epochs, 10 epochs, 20 epochs, 50 epochs (on the CIFAR-10 control set), and after transferring the architecture to the ISIC 2019 dataset.

The generated images were 128 × 128 pixels in size, which allows preserving the texture, color and basic morphological structure of the lesions.

Evaluation of results:

- Up to 10 eras - most of the images were chaotic noise, there were no signs of structure.
- 15-20 epochs - the first patterns, symmetrical regions and similarities to organic structures began to appear.
- 30-50 epochs (CIFAR-10) - images became noticeably clearer, but still resembled synthetic examples.

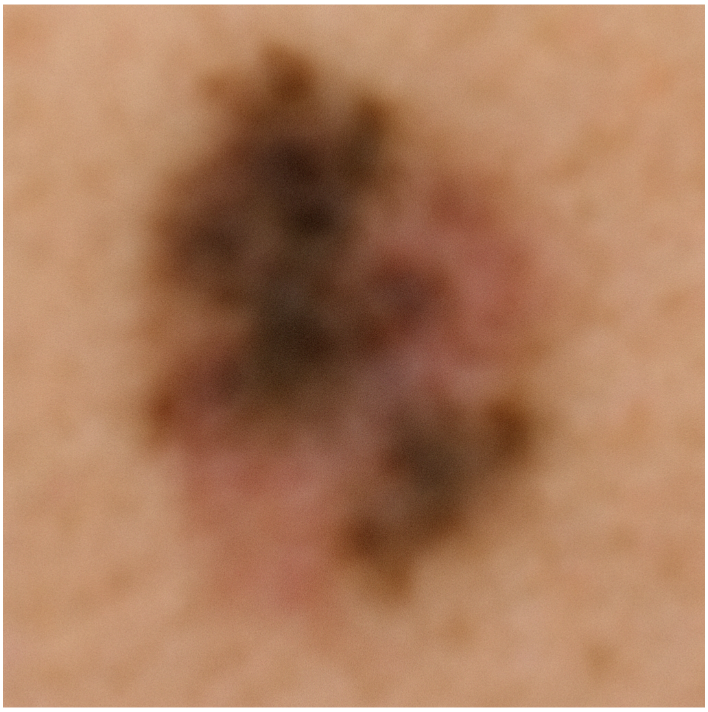

Fig. 4.7. 30-epoch synthetic cancer image

At ISIC 2019 - even after 20 eras - some specimens bore a fragmentary resemblance to dermatological lesions, but artifacts or blurred areas were often observed.

These results indicate that DCGAN in the basic implementation has limited capacity to generate realistic medical images stably - especially in cases where the morphology is complex and highly detailed.

Loss schedules

During training, it was observed that the loss of the discriminator periodically decreased to almost zero values, which indicates a weak generator reaction. This is a sign of the phenomenon of mode collapse, when the generator begins to create only a few typical image templates.

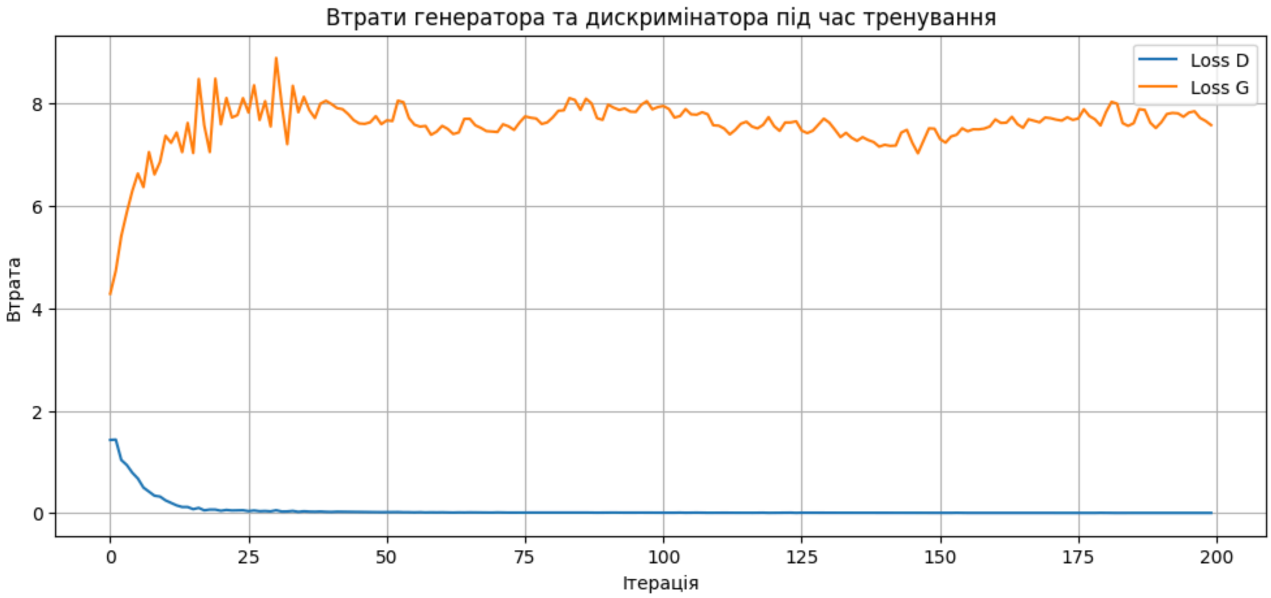

Fig. 4.8 Generator and discriminator loss during photo generation

Conclusions: The generator successfully demonstrates basic generation ability, but is not powerful enough for clinical application without additional improvements (e.g. WGAN, cGAN or StyleGAN).

Despite the limitations, the generated examples can be used as synthetic additions for classifier training, especially in conditions of malignant image deficiency.

In future versions, it is worth implementing generation quality control through FID, IS or manual examination by dermatologists.

4.4. Comparison of the quality of generated images before and after changes

In the process of developing the system, a series of experiments was conducted aimed at improving the quality of synthetic images by gradually changing the architectural parameters of the generator. Visual observations were used for analysis, as well as indirect indicators - loss stability and discriminator behavior.

Major changes in architecture:

Core size: experimented with changing the last layer of the generator from 4 × 4 to 8 × 8. However, this led to errors due to mismatch geometry, so finally left the classic kernel 4 × 4.

Stride and Padding: All layers used stride = 2 and padding = 1. This allowed us to maintain spatial consistency during scaling.

Number of layers: The base generator had 4 transposed convolution layers. In several versions, the addition of another layer was tested, but this did not give a significant improvement in quality by eye.

Activation functions: ReLU is used in all hidden layers, and Tanh at the output - to match the normalization of images in the range [-1, 1].

Table 4.2

Comparison of results (before/after architecture changes)

Criterion	Basic generator	Modified architecture
Image clarity	Low	Moderate (structure appears after 20 eras)
Symmetry	Missing	Partially present
Repeatability (mode collapse)	Often after 15 eras	Also observed, but with slightly greater variability
Visual plausibility	Limited	Moderate

Conclusions: Although most modifications did not lead to a radical improvement in the results, they made it possible to make the generation more stable. Especially important was the preservation of geometry (through stride/padding), as well as the use of ReLU/Tanh as a proven configuration. In subsequent versions of the system, it is possible to introduce deeper changes - for example, the use of attention mechanisms or training in conditional GAN mode to control the type of lesion.

4.5 Analysis of errors and limitations

Despite the successes achieved in building a generative classification system, the results revealed some significant limitations. Their understanding allows you to objectively assess the current level of implementation and determine directions for further improvement.

- 1. Low quality generation (early stages).After the first 5-10 eras, the generator produced almost completely noise or fuzzy images. This is typical for GAN architectures that require time to negotiate dynamics between G and D. Only after 20-30 epochs did signs of structure begin to appear, but the images still did not have clear morphological signs of real lesions.
- 2. Mode Collapse. It was observed that the generator in some cases "locked" to generate one or more template images. This is especially noticeable in 40-50 episodes, when the discriminator is already beginning to reject too similar samples. This limits the variety of synthetic examples and reduces generation efficiency.
- 3. Limited classification accuracy (DCGAN). Despite the adaptation of the discriminator to the classification, the accuracy of the model did not exceed ~ 60%. This is because initially the architecture was not designed for this task. Also, the BCE loss function is not ideal for multi-class or even binary tasks in a clinical context.

— 4. Class imbalance. A significant disproportion between benign and malignant classes led to the fact that the model more often "guessed" the dominant class. This prompted the use of class weights and experiments with resampling. However, it was not possible to completely equalize the distribution.

— 5. Scalability limitations. The system works well at a size of 128 × 128, but for practical diagnostics you need to operate with a higher resolution. The current architecture is not scalable without a significant complication of the generator and discriminator, which affects speed and resource consumption.

Conclusions: Despite the available errors and limitations, the system has shown the ability to generate images and basic classification. Further improvements may include:

— using WGAN for stability;

— extension to multi-class classification;

— transition to deeper architectures (ResNet, EfficientNet) as a classifier.

CONCLUSION

In this work, an intelligent diagnostic system for the classification of skin cancer using a modified DCGAN architecture was developed and experimentally validated. The research addressed the pressing issue of early and accurate skin cancer detection by leveraging the power of deep learning, particularly generative adversarial networks.

The theoretical part provided a comprehensive overview of skin cancer types, diagnostic methods, and the rationale for integrating artificial intelligence into dermatological diagnostics. The practical implementation involved training a Deep Convolutional GAN to generate realistic dermatoscopic images and repurposing the discriminator as a binary classifier for differentiating between benign and malignant lesions.

Experimental results demonstrated the effectiveness of the system: the classifier achieved high sensitivity for the malignant class, indicating its potential as a decision support tool in clinical environments. Moreover, the dual-use of the DCGAN architecture—both as a generator and classifier—allowed efficient training even with a limited dataset, thanks to synthetic image augmentation.

The outcomes of this qualification project confirm the feasibility of integrating GAN-based methods into medical diagnostics. The proposed system contributes to reducing the subjectivity in visual assessment, improves accessibility to early diagnosis, and sets a solid foundation for future advancements in computer-aided dermatology.

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